

APPLICATION FOR FEDERAL ASSISTANCE
SF 424 (R&R)

3. DATE RECEIVED BY STATE

State Application Identifier

1. * TYPE OF SUBMISSION

☐ Pre-application ☒ Application ☐ Changed/Corrected Application

2. DATE SUBMITTED

04/17/2012

Applicant Identifier

4. a. Federal Identifier

GRANT10869132

b. Agency Routing Identifier

311, {Schwartz, Carey}

5. APPLICANT INFORMATION

* Organizational DUNS: 092530369

* Legal Name: Regents of the University of California, Los Angeles

Department:

Division:

* Street1: Office of Contract and Grant Administration

Street2: 11000 Kinross Avenue, Suite 211

* City: Los Angeles

County / Parish: Los Angeles County

* State: CA: California

Province:

* Country: USA: UNITED STATES

* ZIP / Postal Code: 90095-1406

Person to be contacted on matters involving this application

Prefix: Mr.

* First Name: Evan

Middle Name:

* Last Name: Garcia

Suffix:

* Phone Number: 310-794-0171

Fax Number: 310-943-1656

Email: ocga3@research.ucla.edu

6. * EMPLOYER IDENTIFICATION (EIN) or (TIN): 956006143

7. * TYPE OF APPLICANT:

H: Public/State Controlled Institution of Higher Education

Other (Specify):

Small Business Organization Type

☐ Women Owned☐ Socially and Economically Disadvantaged

8. * TYPE OF APPLICATION:

☐ New ☒ Resubmission☐ Renewal ☐ Continuation ☐ Revision

If Revision, mark appropriate box(es).

☐ A. Increase Award☐ B. Decrease Award☐ C. Increase Duration☐ D. Decrease Duration☐ E. Other (specify):* Is this application being submitted to other agencies? Yes ☐ No ☒ What other Agencies:

9. * NAME OF FEDERAL AGENCY:

Office of Naval Research

10. CATALOG OF FEDERAL DOMESTIC ASSISTANCE NUMBER: 12.300

TITLE: Basic and Applied Scientific Research

11. * DESCRIPTIVE TITLE OF APPLICANT'S PROJECT:

Machine Reasoning and Intelligence for Naval Sensing

12. PROPOSED PROJECT:

* Start Date

* Ending Date

06/01/2012

05/31/2017

* 13. CONGRESSIONAL DISTRICT OF APPLICANT

CA-030

14. PROJECT DIRECTOR/PRINCIPAL INVESTIGATOR CONTACT INFORMATION

Prefix: Dr.

* First Name: Stanley

Middle Name:

* Last Name: Osher

Suffix:

Position/Title: Professor

* Organization Name: Regents of the University of California, Los Angeles

Department: Mathematics

Division: Physical Sciences

* Street1: Box 951555

Street2:

* City: Los Angeles

County / Parish: Los Angeles County

* State: CA: California

Province:

* Country: USA: UNITED STATES

* ZIP / Postal Code: 90095-1555

* Phone Number: 310-825-1758

Fax Number: 310-206-2679

* Email: sjo@math.ucla.edu

15. ESTIMATED PROJECT FUNDING a. Total Federal Funds Requested <input style="width: 150px;" type="text" value="1,599,998.00"/> b. Total Non-Federal Funds <input style="width: 150px;" type="text" value="0.00"/> c. Total Federal & Non-Federal Funds <input style="width: 150px;" type="text" value="1,599,998.00"/> d. Estimated Program Income <input style="width: 150px;" type="text" value="0.00"/>	16. * IS APPLICATION SUBJECT TO REVIEW BY STATE EXECUTIVE ORDER 12372 PROCESS? a. YES <input type="checkbox"/> THIS PREAPPLICATION/APPLICATION WAS MADE AVAILABLE TO THE STATE EXECUTIVE ORDER 12372 PROCESS FOR REVIEW ON: DATE: <input style="width: 100px;" type="text"/> b. NO <input type="checkbox"/> PROGRAM IS NOT COVERED BY E.O. 12372; OR <input checked="" type="checkbox"/> PROGRAM HAS NOT BEEN SELECTED BY STATE FOR REVIEW
17. By signing this application, I certify (1) to the statements contained in the list of certifications* and (2) that the statements herein are true, complete and accurate to the best of my knowledge. I also provide the required assurances * and agree to comply with any resulting terms if I accept an award. I am aware that any false, fictitious, or fraudulent statements or claims may subject me to criminal, civil, or administrative penalties. (U.S. Code, Title 18, Section 1001) <div style="text-align: center;"><input checked="" type="checkbox"/> * I agree</div> <small>* The list of certifications and assurances, or an Internet site where you may obtain this list, is contained in the announcement or agency specific instructions.</small>	
18. SFLLL or other Explanatory Documentation <div style="display: flex; align-items: center; margin-top: 10px;"><input style="width: 400px;" type="text"/><div style="margin-left: 10px;"><input type="button" value="Add Attachment"/> <input type="button" value="Delete Attachment"/> <input type="button" value="View Attachment"/></div></div>	
19. Authorized Representative <div style="display: flex; justify-content: space-between; margin-top: 10px;"><div>Prefix: <input style="width: 80px;" type="text" value="Mr."/> * First Name: <input style="width: 250px;" type="text" value="Evan"/></div><div>Middle Name: <input style="width: 150px;" type="text"/></div></div> <div style="display: flex; justify-content: space-between; margin-top: 5px;"><div>* Last Name: <input style="width: 450px;" type="text" value="Garcia"/></div><div>Suffix: <input style="width: 100px;" type="text"/></div></div> <div style="margin-top: 5px;">* Position/Title: <input style="width: 350px;" type="text" value="Grant Analyst"/></div> <div style="margin-top: 5px;">* Organization: <input style="width: 450px;" type="text" value="Regents of the University of California, Los Angeles"/></div> <div style="display: flex; justify-content: space-between; margin-top: 5px;"><div>Department: <input style="width: 200px;" type="text" value="Office of Contract & Grant Adm"/></div><div>Division: <input style="width: 200px;" type="text"/></div></div> <div style="margin-top: 5px;">* Street1: <input style="width: 400px;" type="text" value="11000 Kinross Avenue, Suite 102"/></div> <div style="margin-top: 5px;">Street2: <input style="width: 400px;" type="text"/></div> <div style="display: flex; justify-content: space-between; margin-top: 5px;"><div>* City: <input style="width: 250px;" type="text" value="Los Angeles"/></div><div>County / Parish: <input style="width: 250px;" type="text" value="Los Angeles County"/></div></div> <div style="display: flex; justify-content: space-between; margin-top: 5px;"><div>* State: <input style="width: 400px;" type="text" value="CA: California"/></div><div>Province: <input style="width: 150px;" type="text"/></div></div> <div style="display: flex; justify-content: space-between; margin-top: 5px;"><div>* Country: <input style="width: 400px;" type="text" value="USA: UNITED STATES"/></div><div>* ZIP / Postal Code: <input style="width: 150px;" type="text" value="90095-1406"/></div></div> <div style="display: flex; justify-content: space-between; margin-top: 5px;"><div>* Phone Number: <input style="width: 150px;" type="text" value="310-794-0171"/></div><div>Fax Number: <input style="width: 150px;" type="text" value="310-943-1656"/></div></div> <div style="margin-top: 5px;">* Email: <input style="width: 450px;" type="text" value="ocga3@research.ucla.edu"/></div> <div style="display: flex; justify-content: space-between; margin-top: 20px;"><div style="width: 45%;">* Signature of Authorized Representative <div style="border: 1px solid black; padding: 5px; text-align: center; margin-top: 10px;">Evan Garcia</div></div><div style="width: 45%;">* Date Signed <div style="border: 1px solid black; padding: 5px; text-align: center; margin-top: 10px;">04/17/2012</div></div></div>	
20. Pre-application <input style="width: 300px;" type="text"/> <div style="margin-left: 10px;"><input type="button" value="Add Attachment"/> <input type="button" value="Delete Attachment"/> <input type="button" value="View Attachment"/></div>	

* ORGANIZATIONAL DUNS: 0925303690000

* Budget Type: ☒ Project ☐ Subaward/Consortium

Enter name of Organization: Regents of the University of Ca

Delete Entry

* Start Date: 06/01/2012 * End Date: 09/30/2012

Budget Period 1

A. Senior/Key Person

	Prefix	* First Name	Middle Name	* Last Name	Suffix	* Project Role	Base Salary (\$)	Cal. Months	Acad. Months	Sum. Months	* Requested Salary (\$)	* Fringe Benefits (\$)	* Funds Requested (\$)
1.	Dr.	Stanley		Osher		PD/PI	(b)(4)				0.00	0.00	0.00
2.	Dr.	Andrea		Bertozzi		Co-PD/PI					0.00	0.00	0.00
3.													
4.													
5.													
6.													
7.													
8.													
9.	Total Funds requested for all Senior Key Persons in the attached file												
												Total Senior/Key Person	0.00

Additional Senior Key Persons:

Add Attachment

Delete Attachment

View Attachment

B. Other Personnel

* Number of Personnel	* Project Role	Cal. Months	Acad. Months	Sum. Months	* Requested Salary (\$)	* Fringe Benefits (\$)	* Funds Requested (\$)
<input type="text" value="2"/>	Post Doctoral Associates	<input type="text" value="3.00"/>	<input type="text"/>	<input type="text"/>	(b)(4)		
<input type="text" value="3"/>	Graduate Students	<input type="text"/>	<input type="text"/>	<input type="text" value="3.00"/>			
<input type="text"/>	Undergraduate Students	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>
<input type="text"/>	Secretarial/Clerical	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>
<input type="text"/>		<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>
<input type="text"/>		<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>
<input type="text"/>		<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>
<input type="text"/>		<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>
<input type="text"/>		<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>
<input type="text"/>		<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>
<input type="text" value="5"/>	Total Number Other Personnel				Total Other Personnel		<input type="text" value="(b) (4)"/>
		Total Salary, Wages and Fringe Benefits (A+B)					<input type="text" value="40,088.00"/>

RESEARCH & RELATED Budget {A-B} (Funds Requested)

RESEARCH & RELATED BUDGET - SECTION C, D, & E, BUDGET PERIOD 1

* ORGANIZATIONAL DUNS: 0925303690000

* Budget Type: ☒ Project ☐ Subaward/Consortium

Enter name of Organization: Regents of the University of Ca

Delete Entry

* Start Date: 06/01/2012 * End Date: 09/30/2012 Budget Period 1

C. Equipment Description

List items and dollar amount for each item exceeding \$5,000

	Equipment item	* Funds Requested (\$)
1.		
2.		
3.		
4.		
5.		
6.		
7.		
8.		
9.		
10.		
11.	Total funds requested for all equipment listed in the attached file	
	Total Equipment	

Additional Equipment:

Add Attachment**Delete Attachment****View Attachment****D. Travel****Funds Requested (\$)**

1. Domestic Travel Costs (Incl. Canada, Mexico and U.S. Possessions)	1,250.00
2. Foreign Travel Costs	1,250.00
Total Travel Cost	2,500.00

E. Participant/Trainee Support Costs**Funds Requested (\$)**

1. Tuition/Fees/Health Insurance	
2. Stipends	
3. Travel	
4. Subsistence	
5. Other	
Number of Participants/Trainees	Total Participant/Trainee Support Costs

RESEARCH & RELATED Budget {C-E} (Funds Requested)

RESEARCH & RELATED BUDGET - SECTION F-K, BUDGET PERIOD 1

Next Period

* ORGANIZATIONAL DUNS: 0925303690000

* Budget Type: ☒ Project ☐ Subaward/Consortium

Enter name of Organization: Regents of the University of Ca

Delete Entry

Start Date: 06/01/2012 * End Date: 09/30/2012 Budget Period

F. Other Direct Costs

Funds Requested (\$)

1. Materials and Supplies	403.00
2. Publication Costs	61.00
3. Consultant Services	
4. ADP/Computer Services	
5. Subawards/Consortium/Contractual Costs	112,500.00
6. Equipment or Facility Rental/User Fees	
7. Alterations and Renovations	
8. Computer & Computing Supplies	5,000.00
9.	
10.	

Total Other Direct Costs 117,964.00

G. Direct Costs

Funds Requested (\$)

Total Direct Costs (A thru F) 160,552.00

H. Indirect Costs

Indirect Cost Type	Indirect Cost Rate (%)	Indirect Cost Base (\$)	* Funds Requested (\$)
1. Research On Campus	(b)(4)		39,448.00
2.			
3.			
4.			

Total Indirect Costs 39,448.00

Cognizant Federal Agency (b) (6)

(Agency Name, POC Name, and POC Phone Number)

I. Total Direct and Indirect Costs

Funds Requested (\$)

Total Direct and Indirect Institutional Costs (G + H)

200,000.00

J. Fee

Funds Requested (\$)

K. * Budget Justification COST_ELEMENT_SUMMARY_4_17_121017029068

(Only attach one file.)

Add Attachment

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View Attachment

RESEARCH & RELATED Budget {F-K} (Funds Requested)

Previous Period

RESEARCH & RELATED BUDGET - SECTION A & B, BUDGET PERIOD 2

* ORGANIZATIONAL DUNS: 0925303690000

* Budget Type: ☒ Project ☐ Subaward/Consortium

Enter name of Organization: Regents of the University of Ca

Delete Entry

* Start Date: 10/01/2012 * End Date: 09/30/2013

Budget Period 2

A. Senior/Key Person

	Prefix	* First Name	Middle Name	* Last Name	Suffix	* Project Role	Base Salary (\$)	Cal. Months	Acad. Months	Sum. Months	* Requested Salary (\$)	* Fringe Benefits (\$)	* Funds Requested (\$)
1.	Dr.	Stanley		Osher		PD/PI	(b)(4)			1.00	(b)(4)		
2.	Dr.	Andrea		Bertozzi		Co-PD/PI			0.50				
3.													
4.													
5.													
6.													
7.													
8.													

9. Total Funds requested for all Senior Key Persons in the attached file

Total Senior/Key Person (b)(4)

Additional Senior Key Persons:

Add Attachment

Delete Attachment

View Attachment

B. Other Personnel

* Number of Personnel	* Project Role	Cal. Months	Acad. Months	Sum. Months	* Requested Salary (\$)	* Fringe Benefits (\$)	* Funds Requested (\$)
	Post Doctoral Associates						
1	Graduate Students		9.00	3.00	(b)(4)		
	Undergraduate Students						
	Secretarial/Clerical						
1	Total Number Other Personnel						

Total Other Personnel (b)(4)

Total Salary, Wages and Fringe Benefits (A+B) 71,276.00

RESEARCH & RELATED BUDGET - SECTION C, D, & E, BUDGET PERIOD 2

* ORGANIZATIONAL DUNS: 0925303690000

* Budget Type: ☒ Project ☐ Subaward/Consortium

Enter name of Organization: Regents of the University of Ca

Delete Entry

* Start Date: 10/01/2012 * End Date: 09/30/2013 Budget Period 2

C. Equipment Description

List items and dollar amount for each item exceeding \$5,000

	Equipment item	* Funds Requested (\$)
1.		
2.		
3.		
4.		
5.		
6.		
7.		
8.		
9.		
10.		
11.	Total funds requested for all equipment listed in the attached file	
	Total Equipment	

Additional Equipment:

Add Attachment**Delete Attachment****View Attachment****D. Travel****Funds Requested (\$)**

1.	Domestic Travel Costs (Incl. Canada, Mexico and U.S. Possessions)	2,603.00
2.	Foreign Travel Costs	2,602.00
	Total Travel Cost	5,205.00

E. Participant/Trainee Support Costs**Funds Requested (\$)**

1.	Tuition/Fees/Health Insurance	
2.	Stipends	
3.	Travel	
4.	Subsistence	
5.	Other	
	Number of Participants/Trainees	
	Total Participant/Trainee Support Costs	

RESEARCH & RELATED Budget {C-E} (Funds Requested)

RESEARCH & RELATED BUDGET - SECTION F-K, BUDGET PERIOD 2

Next Period

* ORGANIZATIONAL DUNS: 0925303690000

* Budget Type: ☒ Project ☐ Subaward/Consortium

Enter name of Organization: Regents of the University of Ca

Delete Entry

Start Date: 10/01/2012 * End Date: 09/30/2013 Budget Period 2

F. Other Direct Costs

- Materials and Supplies
- Publication Costs
- Consultant Services
- ADP/Computer Services
- Subawards/Consortium/Contractual Costs
- Equipment or Facility Rental/User Fees
- Alterations and Renovations

- Grad Fees & NRT
- Computing
-

Funds Requested (\$)

(b) (4)

Total Other Direct Costs 180,010.00

G. Direct Costs

Funds Requested (\$)

Total Direct Costs (A thru F) 256,491.00

H. Indirect Costs

	Indirect Cost Type	Indirect Cost Rate (%)	Indirect Cost Base (\$)	* Funds Requested (\$)
1.	Research On Campus	(b) (4)	(b) (4)	43,508.00
2.				
3.				
4.				
Total Indirect Costs				43,508.00

Cognizant Federal Agency (b)(4)

(Agency Name, POC Name, and POC Phone Number)

I. Total Direct and Indirect Costs

Funds Requested (\$)

Total Direct and Indirect Institutional Costs (G + H) 299,999.00

J. Fee

Funds Requested (\$)

K. * Budget Justification COST_ELEMENT_SUMMARY_4_17_121017029068

(Only attach one file.)

Add Attachment

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View Attachment

RESEARCH & RELATED Budget {F-K} (Funds Requested)

Previous Period

RESEARCH & RELATED BUDGET - SECTION A & B, BUDGET PERIOD 3

* ORGANIZATIONAL DUNS: 0925303690000

* Budget Type: ☒ Project ☐ Subaward/Consortium

Enter name of Organization: Regents of the University of Ca

Delete Entry

* Start Date: 10/01/2013 * End Date: 09/30/2014

Budget Period 3

A. Senior/Key Person

	Prefix	* First Name	Middle Name	* Last Name	Suffix	* Project Role	Base Salary (\$)	Cal. Months	Acad. Months	Sum. Months	* Requested Salary (\$)	* Fringe Benefits (\$)	* Funds Requested (\$)
1.	Dr.	Stanley		Osher		PD/PI	(b)(4)			1.00	(b)(4)		
2.	Dr.	Andrea		Bertozzi		Co-PD/PI			0.50				
3.													
4.													
5.													
6.													
7.													
8.													
9.	Total Funds requested for all Senior Key Persons in the attached file												

Total Senior/Key Person (b)(4)

Additional Senior Key Persons:

Add Attachment

Delete Attachment

View Attachment

B. Other Personnel

* Number of Personnel	* Project Role	Cal. Months	Acad. Months	Sum. Months	* Requested Salary (\$)	* Fringe Benefits (\$)	* Funds Requested (\$)
	Post Doctoral Associates						
2	Graduate Students		9.00	3.00	(b)(4)		
	Undergraduate Students						
	Secretarial/Clerical						
2	Total Number Other Personnel						

Total Other Personnel (b)(4)

Total Salary, Wages and Fringe Benefits (A+B) 80,594.00

RESEARCH & RELATED BUDGET - SECTION C, D, & E, BUDGET PERIOD 3

* ORGANIZATIONAL DUNS: 0925303690000

* Budget Type: ☒ Project ☐ Subaward/Consortium

Enter name of Organization: Regents of the University of Ca

Delete Entry

* Start Date: 10/01/2013 * End Date: 09/30/2014 Budget Period 3

C. Equipment Description

List items and dollar amount for each item exceeding \$5,000

	Equipment item	* Funds Requested (\$)
1.		
2.		
3.		
4.		
5.		
6.		
7.		
8.		
9.		
10.		
11.	Total funds requested for all equipment listed in the attached file	
	Total Equipment	

Additional Equipment:

Add Attachment**Delete Attachment****View Attachment****D. Travel****Funds Requested (\$)**

1. Domestic Travel Costs (Incl. Canada, Mexico and U.S. Possessions)	2,627.00
2. Foreign Travel Costs	2,627.00
Total Travel Cost	5,254.00

E. Participant/Trainee Support Costs**Funds Requested (\$)**

1. Tuition/Fees/Health Insurance	
2. Stipends	
3. Travel	
4. Subsistence	
5. Other	
Number of Participants/Trainees	Total Participant/Trainee Support Costs

RESEARCH & RELATED Budget {C-E} (Funds Requested)

RESEARCH & RELATED BUDGET - SECTION F-K, BUDGET PERIOD 3

Next Period

* ORGANIZATIONAL DUNS: 0925303690000

* Budget Type: ☒ Project ☐ Subaward/Consortium

Enter name of Organization: Regents of the University of Ca

Delete Entry

Start Date: 10/01/2013 * End Date: 09/30/2014 Budget Period 3

F. Other Direct Costs

Funds Requested (\$)

1. Materials and Supplies
2. Publication Costs
3. Consultant Services
4. ADP/Computer Services
5. Subawards/Consortium/Contractual Costs
6. Equipment or Facility Rental/User Fees
7. Alterations and Renovations

8. Grad Fees & NRT

9.

10.

Total Other Direct Costs 167,206.00

G. Direct Costs

Funds Requested (\$)

Total Direct Costs (A thru F) 253,054.00

H. Indirect Costs

	Indirect Cost Type	Indirect Cost Rate (%)	Indirect Cost Base (\$)	* Funds Requested (\$)
1.	Research On Campus	(b) (4)	(b) (4)	46,947.00
2.				
3.				
4.				
Total Indirect Costs				46,947.00

Cognizant Federal Agency (b)(4)

(Agency Name, POC Name, and POC Phone Number)

I. Total Direct and Indirect Costs

Funds Requested (\$)

Total Direct and Indirect Institutional Costs (G + H)

300,001.00

J. Fee

Funds Requested (\$)

K. * Budget Justification COST_ELEMENT_SUMMARY_4_17_121017029068

(Only attach one file.)

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Delete Attachment

View Attachment

RESEARCH & RELATED Budget {F-K} (Funds Requested)

Previous Period

RESEARCH & RELATED BUDGET - SECTION A & B, BUDGET PERIOD 4

* ORGANIZATIONAL DUNS: 0925303690000

* Budget Type: ☒ Project ☐ Subaward/Consortium

Enter name of Organization: Regents of the University of Ca

Delete Entry

* Start Date: 10/01/2014 * End Date: 05/31/2015

Budget Period 4

A. Senior/Key Person

	Prefix	* First Name	Middle Name	* Last Name	Suffix	* Project Role	Base Salary (\$)	Cal. Months	Acad. Months	Sum. Months	* Requested Salary (\$)	* Fringe Benefits (\$)	* Funds Requested (\$)
1.	Dr.	Stanley		Osher		PD/PI	(b)(4)				0.00	0.00	0.00
2.	Dr.	Andrea		Bertozzi		Co-PD/PI	(b)(4)		0.50		(b)(4)		
3.													
4.													
5.													
6.													
7.													
8.													
9.	Total Funds requested for all Senior Key Persons in the attached file												
												Total Senior/Key Person	(b)(4)

Additional Senior Key Persons:

Add Attachment

Delete Attachment

View Attachment

B. Other Personnel

* Number of Personnel	* Project Role	Cal. Months	Acad. Months	Sum. Months	* Requested Salary (\$)	* Fringe Benefits (\$)	* Funds Requested (\$)
	Post Doctoral Associates						
4	Graduate Students		3.00		(b)(4)		
	Undergraduate Students						
	Secretarial/Clerical						
4	Total Number Other Personnel						(b)(4)
							Total Other Personnel
							Total Salary, Wages and Fringe Benefits (A+B)
							42,480.00

RESEARCH & RELATED BUDGET - SECTION C, D, & E, BUDGET PERIOD

* ORGANIZATIONAL DUNS: 0925303690000

* Budget Type: ☒ Project ☐ Subaward/Consortium

Enter name of Organization: Regents of the University of Ca

Delete Entry

* Start Date: 10/01/2014 * End Date: 05/31/2015 Budget Period 4

C. Equipment Description

List items and dollar amount for each item exceeding \$5,000

	Equipment item	* Funds Requested (\$)
1.		
2.		
3.		
4.		
5.		
6.		
7.		
8.		
9.		
10.		
11.	Total funds requested for all equipment listed in the attached file	
	Total Equipment	

Additional Equipment:

Add Attachment

Delete Attachment

View Attachment

D. Travel

Funds Requested (\$)

1. Domestic Travel Costs (Incl. Canada, Mexico and U.S. Possessions)	1,739.00
2. Foreign Travel Costs	1,739.00
Total Travel Cost	3,478.00

E. Participant/Trainee Support Costs

Funds Requested (\$)

1. Tuition/Fees/Health Insurance	
2. Stipends	
3. Travel	
4. Subsistence	
5. Other	

	Number of Participants/Trainees	Total Participant/Trainee Support Costs	
--	---------------------------------	---	--

RESEARCH & RELATED Budget {C-E} (Funds Requested)

RESEARCH & RELATED BUDGET - SECTION F-K, BUDGET PERIOD 4

Next Period

* ORGANIZATIONAL DUNS: 0925303690000

* Budget Type: ☒ Project ☐ Subaward/Consortium

Enter name of Organization: Regents of the University of Ca

Delete Entry

Start Date: 10/01/2014 * End Date: 05/31/2015 Budget Period 4

F. Other Direct Costs

Funds Requested (\$)

1. Materials and Supplies
2. Publication Costs
3. Consultant Services
4. ADP/Computer Services
5. Subawards/Consortium/Contractual Costs
6. Equipment or Facility Rental/User Fees
7. Alterations and Renovations

8. Grad Fees & NRT

9.

10.

(b)(4)

Total Other Direct Costs 128,635.00

G. Direct Costs

Funds Requested (\$)

Total Direct Costs (A thru F) 174,593.00

H. Indirect Costs

	Indirect Cost Type	Indirect Cost Rate (%)	Indirect Cost Base (\$)	* Funds Requested (\$)
1.	Research On Campus	(b) (4)	(b) (4)	25,406.00
2.				
3.				
4.				

Total Indirect Costs 25,406.00

Cognizant Federal Agency (b)(4)

(Agency Name, POC Name, and POC Phone Number)

I. Total Direct and Indirect Costs

Funds Requested (\$)

Total Direct and Indirect Institutional Costs (G + H)

199,999.00

J. Fee

Funds Requested (\$)

K. * Budget Justification COST_ELEMENT_SUMMARY_4_17_121017029068

(Only attach one file.)

Add Attachment

Delete Attachment

View Attachment

RESEARCH & RELATED Budget {F-K} (Funds Requested)

Previous Period

RESEARCH & RELATED BUDGET - SECTION A & B, BUDGET PERIOD 5

* ORGANIZATIONAL DUNS: 0925303690000

* Budget Type: ☒ Project ☐ Subaward/Consortium

Enter name of Organization: Regents of the University of Ca

Delete Entry

* Start Date: 06/01/2015 * End Date: 05/31/2017

Budget Period 5

A. Senior/Key Person

	Prefix	* First Name	Middle Name	* Last Name	Suffix	* Project Role	Base Salary (\$)	Cal. Months	Acad. Months	Sum. Months	* Requested Salary (\$)	* Fringe Benefits (\$)	* Funds Requested (\$)
1.	Dr.	Stanley		Osher		PD/PI	(b)(4)			2.00	(b)(4)		
2.	Dr.	Andrea		Bertozzi		Co-PD/PI			2.00				
3.													
4.													
5.													
6.													
7.													
8.													
9.	Total Funds requested for all Senior Key Persons in the attached file												
												Total Senior/Key Person	(b)(4)

Additional Senior Key Persons:

Add Attachment

Delete Attachment

View Attachment

B. Other Personnel

* Number of Personnel	* Project Role	Cal. Months	Acad. Months	Sum. Months	* Requested Salary (\$)	* Fringe Benefits (\$)	* Funds Requested (\$)
	Post Doctoral Associates						
1	Graduate Students		9.00	3.00	(b)(4)		
	Undergraduate Students						
	Secretarial/Clerical						
1	Total Number Other Personnel						
							Total Other Personnel
							(b)(4)
							Total Salary, Wages and Fringe Benefits (A+B)
							164,737.00

RESEARCH & RELATED BUDGET - SECTION C, D, & E, BUDGET PERIOD 5

* ORGANIZATIONAL DUNS: 0925303690000

* Budget Type: ☒ Project ☐ Subaward/Consortium

Enter name of Organization: Regents of the University of Ca

Delete Entry

* Start Date: 06/01/2015 * End Date: 05/31/2017 Budget Period 5

C. Equipment Description

List items and dollar amount for each item exceeding \$5,000

	Equipment item	* Funds Requested (\$)
1.		
2.		
3.		
4.		
5.		
6.		
7.		
8.		
9.		
10.		
11.	Total funds requested for all equipment listed in the attached file	
	Total Equipment	

Additional Equipment:

Add Attachment**Delete Attachment****View Attachment****D. Travel****Funds Requested (\$)**

1. Domestic Travel Costs (Incl. Canada, Mexico and U.S. Possessions)	5,725.00
2. Foreign Travel Costs	5,724.00
Total Travel Cost	11,449.00

E. Participant/Trainee Support Costs**Funds Requested (\$)**

1. Tuition/Fees/Health Insurance	
2. Stipends	
3. Travel	
4. Subsistence	
5. Other	

	Number of Participants/Trainees	Total Participant/Trainee Support Costs	
--	---------------------------------	---	--

RESEARCH & RELATED Budget {C-E} (Funds Requested)

RESEARCH & RELATED BUDGET - SECTION F-K, BUDGET PERIOD 5

* ORGANIZATIONAL DUNS: 0925303690000

* Budget Type: ☒ Project ☐ Subaward/Consortium

Enter name of Organization: Regents of the University of Ca

Delete Entry

Start Date: 06/01/2015 * End Date: 05/31/2017 Budget Period 5

F. Other Direct Costs

Funds Requested (\$)

1. Materials and Supplies
2. Publication Costs
3. Consultant Services
4. ADP/Computer Services
5. Subawards/Consortium/Contractual Costs
6. Equipment or Facility Rental/User Fees
7. Alterations and Renovations

8. Grad Fees & NRT
- 9.
- 10.

(b)(4)

Total Other Direct Costs 314,006.00

G. Direct Costs

Funds Requested (\$)

Total Direct Costs (A thru F) 490,192.00

H. Indirect Costs

	Indirect Cost Type	Indirect Cost Rate (%)	Indirect Cost Base (\$)	* Funds Requested (\$)
1.	Research On Campus	(b) (4)	(b) (4)	109,807.00
2.				
3.				
4.				

Total Indirect Costs 109,807.00

Cognizant Federal Agency DHHS, Wallace Chan, 415-437-7820

(Agency Name, POC Name, and POC Phone Number)

I. Total Direct and Indirect Costs

Funds Requested (\$)

Total Direct and Indirect Institutional Costs (G + H) 599,999.00

J. Fee

Funds Requested (\$)

K. * Budget Justification COST_ELEMENT_SUMMARY_4_17_121017029068

(Only attach one file.)

Add Attachment

Delete Attachment

View Attachment

RESEARCH & RELATED Budget {F-K} (Funds Requested)

RESEARCH & RELATED BUDGET - Cumulative Budget

		Totals (\$)
Section A, Senior/Key Person		(b)(4)
Section B, Other Personnel		
Total Number Other Personnel	13	
Total Salary, Wages and Fringe Benefits (A+B)		
Section C, Equipment		
Section D, Travel		
1. Domestic	13,944.00	
2. Foreign	13,942.00	
Section E, Participant/Trainee Support Costs		
1. Tuition/Fees/Health Insurance		
2. Stipends		
3. Travel		
4. Subsistence		
5. Other		
6. Number of Participants/Trainees		
Section F, Other Direct Costs		907,821.00
1. Materials and Supplies	4,993.00	
2. Publication Costs	901.00	
3. Consultant Services		
4. ADP/Computer Services		
5. Subawards/Consortium/Contractual Costs	800,000.00	
6. Equipment or Facility Rental/User Fees		
7. Alterations and Renovations		
8. Other 1	98,927.00	
9. Other 2	3,000.00	
10. Other 3		
Section G, Direct Costs (A thru F)		(b)(4)
Section H, Indirect Costs		
Section I, Total Direct and Indirect Costs (G + H)		
Section J, Fee		

Cost Proposal
ONR BAA 11-001

Proposal Title: Machine Reasoning and Intelligence for Naval Sensing

Submitted by:
Stanley Osher (PI) and Andrea Bertozzi (co-PI)
UCLA
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520 Portola Plaza
6363 Math Sciences Building
Los Angeles, CA 90095-155

Phone: 310-825-4701
Fax: 310-206-2679
Email: {sjo, bertozzi}@math.ucla.edu

Subaward to:

Lawrence Carin (co-PI)
Department of Electrical and Computer Engineering
Duke University
Durham, NC
Email: lcarin@duke.edu

Administrative POC: Evan Garcia
Grant Analyst
UCLA
Office of Contracts and Grants
11000 Kinross Bldg. Ste 102
Los Angeles, CA 90095

Phone: 310-794-0171
Fax: 310-943-1656
Email: ocga3@research.ucla.edu

Time Period:

36 months, \$300K/yr; Two additional years \$300K/yr
Proposed start date: 1 June 2012

COST ELEMENT SUMMARY

Phase 1			
COST ELEMENT	BASE	RATE	AMOUNT
DIRECT LABOR Senior Personnel: Other Personnel:	(b)(4)		
TOTAL DIRECT LABOR			
FRINGE BENEFITS			
TOTAL LABOR OVERHEAD			
SUBCONTRACTOR(S)			
MATERIALS & EQUIPMENT			
MATERIAL OVERHEAD			
TRAVEL			
OTHER DIRECT COSTS (ODC)			
General and Administrative (G&A)			
Independent Research and Development (IR&D)/Bid and Proposal (B&P)			
	\$	%	\$0.00
SUBTOTAL COSTS			\$1,000,000
COST OF MONEY (See DD Form 1861)			\$0.00
TOTAL COST			\$1,000,000
PROFIT/FEE	\$0.00	0%	\$0.00
TOTAL PRICE/COST			\$1,000,000
GOVERNMENT SHARE			\$0.00
RECIPIENT SHARE (if applicable)			\$0.00

Additional Years			
COST ELEMENT	BASE	RATE	AMOUNT
DIRECT LABOR Senior Personnel: Other Personnel:	(b)(4)		
TOTAL DIRECT LABOR			
FRINGE BENEFITS			
TOTAL LABOR OVERHEAD			
SUBCONTRACTOR(S)			
MATERIALS & EQUIPMENT			
MATERIAL OVERHEAD			
TRAVEL			
OTHER DIRECT COSTS (ODC)			
General and Administrative (G&A)			
Independent Research and Development (IR&D)/Bid and Proposal (B&P)	\$	%	\$0.00
SUBTOTAL COSTS			\$600,000
COST OF MONEY (See DD Form 1861)			\$0.00
TOTAL COST			\$600,000
PROFIT/FEE	\$0.00	0%	\$0.00
TOTAL PRICE/COST			\$600,000
GOVERNMENT SHARE			\$0.00
RECIPIENT SHARE (if applicable)			\$0.00

DETAILED COSTS:

	06/01/12 thru 09/30/12	10/01/12 thru 09/30/13	10/01/13 thru 09/30/14	10/01/14 thru 05/31/15	TOTAL
Senior Personnel					
1. Osher, Stan (Summer)	\$0	(b)(4)		\$0	(b)(4)
2. Bertozzi, Andrea (AY)	\$0			(b)(4)	(b)(4)
Total Senior Personnel	\$0				(b)(4)
Other Personnel					
1. Postdoc	(b)(4)	\$0	\$0	\$0	(b)(4)
2. Graduate Student		(b)(4)	(b)(4)	(b)(4)	(b)(4)
Total Salaries					(b)(4)
Fringe Benefits					
Faculty- Summer Yr	\$0	(b)(4)		\$0	(b)(4)
Faculty- Academic Yr	\$0			(b)(4)	(b)(4)
Postdoc	(b)(4)	\$0	\$0		(b)(4)
Student-Summer		(b)(4)	(b)(4)	\$0	(b)(4)
Student-Academic Yr	\$0			(b)(4)	(b)(4)
Non Resident Tuition (NRT)	\$0	(b)(4)	\$0	(b)(4)	(b)(4)
Fee Remission	\$0		(b)(4)		(b)(4)
Fringe Benefits	(b)(4)				(b)(4)
Total Salaries, Benefits					(b)(4)
Travel	\$2,500	\$5,206	\$5,254	\$3,478	\$16,438
Other Direct Costs					
1. Materials & Supplies	(b)(4)	(b)(4)	(b)(4)	(b)(4)	(b)(4)
2. Publication Costs					(b)(4)
3. Equipment items less than \$5K			\$0	\$0	(b)(4)
4. Subaward to Duke			(b)(4)	(b)(4)	(b)(4)
Total Other Costs					(b)(4)
Total Direct Costs	(b)(4)				
Indirect Costs					
Total Costs	\$200,000	\$300,000	\$300,000	\$200,000	\$1,000,000

DETAILED COST ADDITIONAL YEARS

	06/01/15 thru 09/30/15	10/01/15 thru 09/30/16	10/01/16 thru 05/31/17	TOTAL
Senior Personnel				
1. Osher, Stan (Summer)	(b)(4)	(b)(4)	\$0	(b)(4)
2. Bertozzi, Andrea (AY)	\$0		(b)(4)	(b)(4)
Total Senior Personnel	(b)(4)			(b)(4)
Other Personnel				
1. Graduate Student	(b)(4)		\$0	(b)(4)
Total Salaries			(b)(4)	(b)(4)
Fringe Benefits				
Faculty- Summer Yr	(b)(4)		\$0	(b)(4)
Faculty- Academic Yr	\$0	(b)(4)	(b)(4)	(b)(4)
Student-Summer	(b)(4)		\$0	(b)(4)
Student-Academic Yr	\$0	(b)(4)	\$0	(b)(4)
Non Resident Tuition (NRT)	\$0	\$0	\$0	\$0
Fee Remission	\$0	(b)(4)	\$0	(b)(4)
Fringe Benefits	(b)(4)		(b)(4)	(b)(4)
Total Salaries, Benefits				(b)(4)
Travel	(b)(4)			(b)(4)
Other Direct Costs				
1. Materials & Supplies	(b)(4)			(b)(4)
2. Publication Costs				(b)(4)
3. Equipment items less than \$5K	\$0	\$0	\$0	\$0
4. Subaward to Duke	(b)(4)			(b)(4)
Total Other Costs				(b)(4)
Total Direct Costs	(b)(4)			(b)(4)
Indirect Costs				(b)(4)
Total Costs	\$175,000	\$300,000	\$125,000	\$600,000

Budget Justification

SALARY AND WAGES

Salaries and wages have been calculated on the basis of the University of California Academic Salary Schedule and the Staff Personnel Manual Title and Pay Plan for fiscal year 2012-2013. We are projecting a 5% salary increase per year for PI and Co-Pi's, then we are projecting a 2% salary increase per year for remaining personnel for PostDocs and Student Researchers. The PI will be responsible for the overall coordination of the project and the supervision of the graduate students.

	06/01/12-09/30/12	10/1/12-09/30/13	10/01/13-09/30/14	10/01/14-05/31/15
Stanley Osher Starting salary: (b)(4)	No Salary	100% effort, 1.0 mth Summer salary	100% effort, 1.0 mth Summer salary	No Salary
Bertozzi Starting salary: (b)(4)	No Salary	50% effort, .5 mth academic salary	50% effort, .5 mth academic salary	50% effort, .5 mth academic salary

	06/01/15-09/30/15	10/1/15-09/30/16	10/01/16-05/31/17
Stanley Osher Starting salary: (b)(4)	100% effort, 1.0 mth Summer salary	100% effort, 1.0 mth Summer salary	No Salary
Andrea Bertozzi Starting salary: (b)(4)	No Salary	100% effort, 1.0 mth academic salary	100% effort, 1.0 mth academic salary

	06/01/12-09/30/12	10/1/12-09/30/13	10/01/13-09/30/14	10/01/14-05/31/15
Postdoc Starting salary: (b)(4)	2 Postdocs 54% for 3 mths	No Salary	No Salary	No Salary
GSR Starting salary: (b)(4)	3 students 50% during summer months	1 student 50% during academic, then 1 student 50% during summer months	1 student 50% during academic, then 2 students 50% summer months	4 students 50% during Fall Qtr academic

	06/01/15-09/30/15	10/1/15-09/30/16	10/01/16-05/31/17
GSR Starting salary: (b)(4)	1 student 75% during summer months	1 student 50% during academic for two qtrs, then 1 student 50% during summer	No Salary

BENEFITS

Fringe benefits are calculated according to the following rates:

Faculty:	(academic)	(b) (4)
	(summer)	(b) (4)
Postdoc:	(academic)	(b) (4)
Graduate Student Researchers:	(academic)	(b) (4)
	(summer)	(b) (4)

TRAVEL

Funds will be used to reimburse the Principal Investigator, Co-Principal Investigators and graduate students affiliated with the project, for the actual cost of research related travel to attend the regular group meetings, and also conferences and workshops related to the theme of the project. Some of the funds may be used to pay for the actual travel expenses of the visitors to the group. Travel will be at various conferences worldwide, locations to be determined at a later date. Rates for travel are based off historical data.

SUPPLIES AND EXPENSES

1. MATERIALS AND SUPPLIES

These funds will be used to purchase goods and services necessary to conduct the research pricing based on historical data. These funds will also be used to cover the campus mandated Technology Infrastructure Fee (TIF) of \$41.58/month per employee for each employee supported by this proposed grant.

2. PUBLICATION COSTS/DOCUMENTATION/DISSEMINATION

Funds will be used for publication costs may include artwork, page charges, reprints, postage, and photocopying. (Postage and photocopying are requested to fund duplication and mail of reprints of grant publications and related research documents to requesters.)

3. COMPUTER/COMPUTING EQUIPMENT

In the Period 1 and 2 of the budget we are requesting funds for laptop, desktop computer and computing supplies pricing based on historical data.

SUBAWARDS

Subaward to Dr. Lawrence Carin of Duke University for a total of \$500,000. Please see attached budget.

OTHER

Graduate Student the required fee remission of (b) (4) for three quarters for one student and the Non-Resident Tuition for two quarters for one student in Budget Period 2 and for three quarters in Period 4. With a 5% inflation a year. Rates can be found at www.gdnet.ucla.edu/gss/library/1112gradfees.pdf.

FACILITIES AND ADMINISTRATIVE COST RATES

(b) (4) MTDC (excluding fee remission, non-resident tuition and Participant Support). Our rates were approved by U.S.D.H.H.S. (the responsible Federal audit agency) on April 27, 2011.

Name (PI) Carin, Duke University

Start date: 06/01/12

End date: 05/31/17

		Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7	Total
		6/1/2012 - 09/30/2012	10/1/2012-09/30/13	10/1/13 - 09/30/14	10/1/14 - 05/31/15	6/1/15 - 09/30/15	10/1/15 - 09/30/16	10/1/16 - 05/31/17	6/1/12 - 5/31/17
		6 mos	12 mos	12 mos	8 mos	4 mos	12 mos	8 mos	
Salaries		<div>(b) (4)</div>							<div>(b) (4)</div>
PI	L. Carin								
Labor Rate									
Labor Hours									
Post Doctoral Associate	PD								
Labor Rate									
Labor Hours									
Graduate Research Assistant	Grad RA								
Labor Rate									
Labor Hours									
Total									
PI Fringe benefits	<div>(b) (4)</div>								
Post Doc Fringe	<div>(b) (4)</div>								
PhD Fringe benefits	<div>(b) (4)</div>								
Total Salaries									
Travel									
Tuition Remission									
Modified Direct Costs									
Total Direct Costs									
Indirect <div>(b) (4)</div>									
Total Project Costs		\$112,500	\$150,000	\$150,000	\$87,500	\$87,500	\$150,000	\$62,500	\$800,000

Research Staff. Prof. Lawrence Carin, serving as the Principal Investigator (PI), will oversee and direct the proposed research and coordinate the results and direction of the program with the sponsor. The full-time equivalent of 1.0 month's salary in years one through three Base Period and in years four and five Option Period are requested for the PI's support.

The PI will be supported by one Postdoctoral Associate and one Graduate Student Research Assistant. The Postdoc will provide 3.05 months in year one, 5.64 months in year two, 6.20 months in year three, 3.40 months in year four and 3.2 months in year five. The Postdoc will do the computer programming for modeling, simulations, and modeling effectiveness evaluation. The Graduate Research Assistant will develop nonparametric Bayesian methods for analysis of general acoustic sensing data at 100% level of effort each year.

The basis of the labor rate for Dr. Carin is the Institutional Base Salary (IBS, *aka* Academic Year or nine-month salary) as set annually by the Dean of Pratt School of Engineering and as approved by the Office of the Provost. For Duke's fiscal year beginning July 1, 2011, Dr. Carin's IBS will be (b) (4). The following years are projected on a basis of a 3% increase per year.

The basis of the labor rates for the Postdoctoral Assistant is the amount specified in the respective appointment letter, which is negotiated annually between the individual and the faculty advisor considering education, experience, and skills, and as approved by the Chair of Electrical and Computer Engineering. For Year 1, the annual salary level for the Research Scientist is projected to be (b) (4). The following years are projected on the basis of a 3% increase per year.

The basis of the labor rate for graduate student Research Assistant (RA) is the minimum salary levels for Research Assistants as set by the Office of the Dean in the Pratt School of Engineering, and as adjusted by Electrical and Computer Engineering (ECE) Department policy. All support for RAs at Duke University is paid as wages as required by federal regulations and is treated like all other University wages with the ones exception that lower fringe benefit rates are assessed. For Duke's fiscal year beginning July 1, 2010, the twelve month compensation level for RAs in ECE is projected to be (b) (4) for years one and two with a 3% increase projected in year three of the project.

All of the proposed research staff are paid on a monthly basis and are FLSA-exempt employees. The proposed levels of effort and mixes of labor types are based on prior experience with projects of similar scope and comparable complexity.

Fringe Benefits. Duke University's projected fringe benefit rates applicable to the PI's salary are (b) (4) in year one and (b) (4) in year two, and (b) (4) in year three.

For the Postdoctoral Associate, the fringe benefit rates are (b) (4) in year one, (b) (4) in year two, and (b) (4) in year three.

For the Graduate Research Assistant, the fringe benefit rates are (b) (4) in year one, (b) (4) in year two and (b) (4) in year three.

Travel costs. Support is requested for the PI and/or Post doctoral Associate to travel to Arlington, VA or other designated locale for program reviews and technical meetings as needed.

For each trip to Arlington, VA, \$158 is estimated for the air fare (per person); \$78 (x1), rental car; \$10 (x1), parking; \$17.00 (per person), local mileage; \$71/day x 1.0 days/trip (per person), per diem; total, approximately \$334/person. Two, one-day trips are planned for the PI and one, one-day trip is planned for the Postdoctoral Associate each year.

For each trip to Los Angeles, California, \$358 is estimated for the airfare (per person); \$78 (X3) rental car; \$10 (X3), parking; \$17.00 (per person), local mileage; \$123 (x2), lodging; \$71 (X3), per diem; approximately \$1,098/person. One, three day trip is planned for the PI to Los Angeles California each year.

Tuition Remission-IDC Exempt. For the 2010-2011 academic year, tuition remission is set at (b) (4) each semester. These rates are set by the Graduate School and are applied consistently across the University, regardless of funding source. Amounts for subsequent academic years are projected to increase 4% each year. The amount that will be incurred during the applicable academic terms in proposed periods of performance will be (b) (4) in year one, (b) (4) in year two, and (b) (4) in year three.

Facilities and Administrative (F&A) costs. The DHHS federally negotiated Facilities and Administrative (F&A) cost rate is used. Indirect costs for an on-campus research project are charged at Duke University's negotiated rate of (b) (4) of modified total direct costs (MTDC), equal to total direct costs minus capital equipment costs, student tuition remission, patient care costs, rental costs of off-site facilities, and subaward costs above the first (b) (4) of each individual subaward.

RESEARCH & RELATED Other Project Information

1. * Are Human Subjects Involved? ☐ Yes ☒ No

1.a If YES to Human Subjects

Is the Project Exempt from Federal regulations? ☐ Yes ☐ No

If yes, check appropriate exemption number. ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6

If no, is the IRB review Pending? ☐ Yes ☐ No

IRB Approval Date:

Human Subject Assurance Number:

2. * Are Vertebrate Animals Used? ☐ Yes ☒ No

2.a. If YES to Vertebrate Animals

Is the IACUC review Pending? ☐ Yes ☐ No

IACUC Approval Date:

Animal Welfare Assurance Number

3. * Is proprietary/privileged information included in the application? ☐ Yes ☒ No

4.a. * Does this project have an actual or potential impact on the environment? ☐ Yes ☒ No

4.b. If yes, please explain:

4.c. If this project has an actual or potential impact on the environment, has an exemption been authorized or an environmental assessment (EA) or environmental impact statement (EIS) been performed? ☐ Yes ☐ No

4.d. If yes, please explain:

5. * Is the research performance site designated, or eligible to be designated, as a historic place? ☐ Yes ☒ No

5.a. If yes, please explain:

6. * Does this project involve activities outside of the United States or partnerships with international collaborators? ☐ Yes ☒ No

6.a. If yes, identify countries:

6.b. Optional Explanation:

7. * Project Summary/Abstract

8. * Project Narrative

9. Bibliography & References Cited

10. Facilities & Other Resources

11. Equipment

12. Other Attachments ☐

Project Summary

A research program is proposed in which leading researchers from UCLA and Duke will team to address the problem of Machine Reasoning and Intelligence for Naval Sensing Applications. The proposed team, summarized in Fig. 1, brings together a set of skills that are singular in their own right, and integrated as proposed will leverage synergies to unify several emerging areas of applied mathematics and statistics for machine learning and intelligence. The proposed program has a statistical underpinning, enabling automated systems to provide multiple hypotheses that are (i) consistent with a mission; (ii) support the use of data that is uncertain, incomplete, imprecise, and contradictory (UIIC); (iii) provide a capability to suggest experiments or courses of action that disambiguate between hypotheses; (iv) identify data with appropriate data quality; and (v) represent UIIC data and support efficient computation as well as hypothesis formulation.

Technical Proposal
ONR BAA 11-001

Proposal Title: Machine Reasoning and Intelligence for Naval Sensing

Submitted by:
Stanley Osher (PI) and Andrea Bertozzi (co-PI)
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Subaward to:

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Administrative POC: Evan Garcia
Grant Analyst
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Office of Contracts and Grants
11000 Kinross Bldg. Ste 102
Los Angeles, CA 90095

Phone: 310-794-0171
Fax: 310-943-1656
Email: ocga3@research.ucla.edu

Time Period:

36 months, \$300K/yr; Two additional years \$300K/yr
Proposed start date: 1 June 2012

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1 Future Naval Relevance

1.1 Program goals and objectives as they relate to the US Navy

A research program is proposed in which leading researchers from UCLA and Duke will team to address the problem of *Machine Reasoning and Intelligence for Naval Sensing Applications*. The proposed team, summarized in Fig. 1, brings together a set of skills that are singular in their own right, and integrated as proposed will leverage synergies to unify several emerging areas of applied mathematics and statistics for machine learning and intelligence. The proposed program has a statistical underpinning, enabling automated systems to provide multiple hypotheses that are (i) consistent with a mission; (ii) support the use of data that is uncertain, incomplete, imprecise, and contradictory (UIC); (iii) provide a capability to suggest experiments or courses of action that disambiguate between hypotheses; (iv) identify data with appropriate data quality; and (v) represent UIC data and support *efficient* computation as well as hypothesis formulation.

The proposed methods are statistical in nature, with analysis to be performed within both an optimization and Bayesian setting. The former is typically a maximum *a posterior* (MAP) representation of the latter, and this linkage will be leveraged within the proposed program to unify what heretofore have been two distinct and independent research directions. As an example of how such statistical constructs will be employed within the proposed research, Prof. Bertozzi has recently made significant contributions on analyzing space-time human behavior, of relevance to counter-insurgency and other modern military activities (her work has focused on gang behavior in major cities). The graphical models developed in that research are well suited for the nonparametric Bayesian models being developed by Prof. Carin. Specifically, a new class of Bayesian models are being developed that explicitly leverage graphical information, for example in the form of geography and time. Profs. Bertozzi and Carin have for example recently analyzed human behavior (voting) within the US Congress [1], and these analyses explicitly impose graphical information in the form of geographical locations between congressional districts, as well as time evolution. Such analyses also naturally allow development of methods for incorporating metadata, such as the party of the congressman, and the demographics of his/her congressional district. Finally, we may use such data to investigate exploitation of HUMINT, here in the form of documents characteristic of particular legislation.

Within the proposed program we will couple and unify the statistical methods developed independently by the UCLA and Duke team members. The proposed representations will naturally include a characterization of uncertainty, incompleteness, and imprecision in the data, enabling an understanding of these effects on downstream processing or control of these quantities. As indicated above, the proposed methods and representations will be capable of being instantiated with data from single or multiple sensors as well as unstructured data sources and HUMINT.

Building upon our ongoing research on analysis of unconventional data associated with criminal behavior, while also relating such data to HUMINT (*e.g.*, documents, historical records, and open-source information), we will develop new automated methods for mission-relevant identification, discovery, and representation of relationships, intentions,

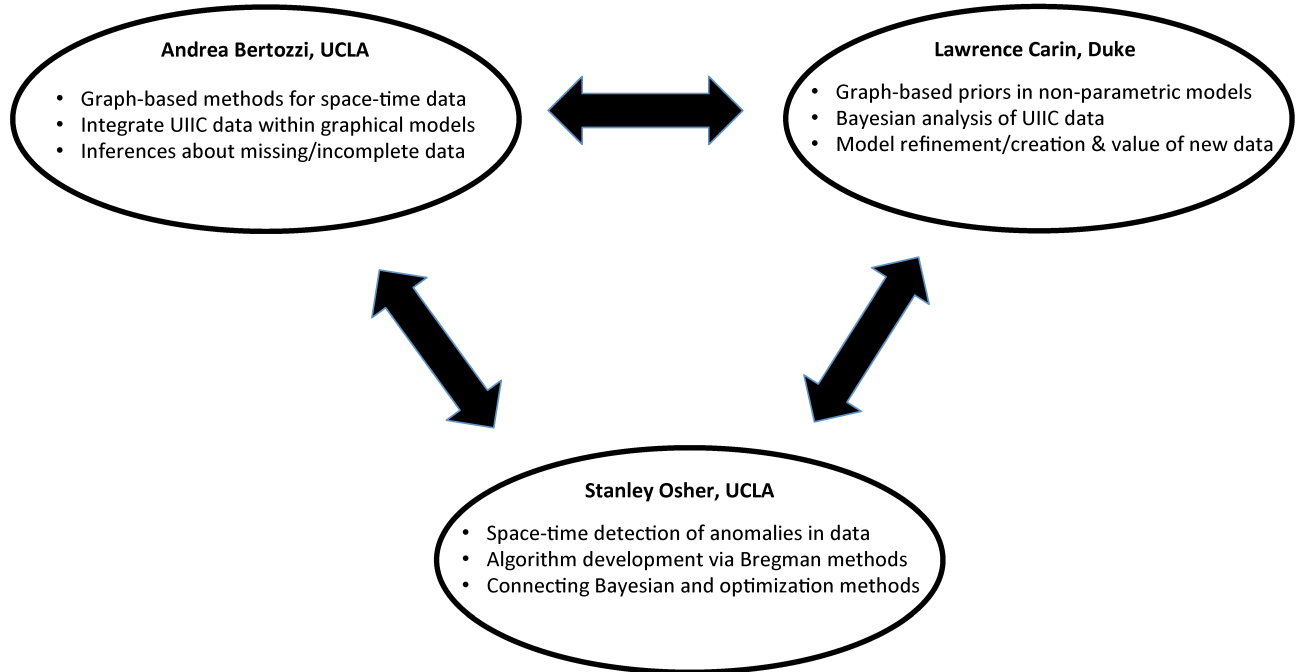


Figure 1: The proposed team will integrate distinct and complementary tools to address the challenge of machine reasoning and intelligence. Profs. Bertozzi and Carin will analyze unconventional sources of data, including space-time patterns of human behavior, unstructured data, and HUMINT, while integrating such with traditional sensor data. The graphical constructs developed by Prof. Bertozzi will be integrated as nonparametric priors within the Bayesian formalisms of Prof. Carin. The latter methods will also quantify the value of information, of importance for defining which new data should be acquired to refine inferences, reduce uncertainty on models, and possibly spawn new models. Prof. Osher will constitute the foundation of the proposed program, as his computational tools will make the proposed statistical algorithms tractable for accurate machine reasoning. The Bregman optimization approaches will be integrated within the statistical models developed by Profs. Bertozzi and Carin. We will also seek to connect optimization and Bayesian approaches, with variational methods playing an important role. The unification of statistical, Bayesian and optimization methods will be a fundamental product of the proposed program. Additionally, Prof. Osher will develop new techniques for inferring the presence of anomalies in general space-time-spectral data, extending ideas in robust PCA.

and objectives from unstructured open source data. These automated methods for a fixed mission will support analysis of existing relationships, intentions, and objectives and synthesis of new relationships, intentions, and objectives in the context of a mission, as well as changes in relationships, intentions, and objectives.

A key driver of the proposed technology is that while the data may be inherently high-dimensional, it typically may be represented in terms of models with low-dimensional structure [1]. A unifying theme of the proposed research therefore concerns exploitation of *low-dimensional structure* for representation and inference with high-dimensional data. Means by which this low-dimensional structure will be inferred and leveraged include: (i) reducing the quantity of data needed for learning, yielding robustness to noise, missing and incomplete data, and contradictory information; (ii) the low-dimensional latent space is of-

ten shared between different types of heterogeneous data, and therefore data with different alphabets may be analyzed jointly by sharing latent structure; (iii) low-dimensional representations such as low-rank models are ideal for inferences of anomalies, characterized by data that are inconsistent with the low-dimensional subspace in which data typically reside (*e.g.*, robust-PCA [2, 3]); (iv) the low-dimensional representations may significantly accelerate computations with high-dimensional data, using methods such as stochastic gradients [4], which we will here extend to Bayesian formalisms via variational Bayesian analysis.

The proposed strategies and techniques are naturally capable of autonomous reasoning that leads to validation of an existing model, adapting an existing model, or synthesizing a new model that is consistent with the data in the context of the mission. Specifically, the proposed Dirichlet process [5] and beta process models [6] naturally adapt and refine existing models as new data are acquired, updating the probability that particular models are consistent with (potentially heterogeneous and contradictory) data observations. Further, these models nonparametrically infer whether new models (hypotheses) should be constituted (via the Dirichlet process) and whether new representational model features are required (via the beta process). These automated reasoning methods are capable of adapting the underlying models via concept drift, inferring which experiences from the past are relevant to the present, and which are not. In addition to the Dirichlet and beta processes, we will investigate new models that constitute power-law behavior (Pitman-Yor and stable-beta processes) over space and time, of interest for analysis of rare but important events.

We also propose a new class of computational architectures that support the research efforts described above, and that will make inference fast. Specifically, we will build upon Prof. Osher’s recent significant developments with Bregman-type methods, see *e.g.*, [7, 8] and the references therein. We will employ these methods in the proposed machine learning and statistical models. Of particular importance is the conversion of Bayesian inference to optimization via variational Bayesian analysis. The Bregman methods will provide a new and accurate means of performing such approximate Bayesian inference, in the context of the sophisticated models discussed above. These statistical methods allow one to rigorously compute measures such as risk, yielding explicit computation of the value of information in the context of any given mission; these methods will quantify where the available information is sufficient and of appropriate quality, sufficient but not of appropriate quality, or insufficient to support reasoning with regard to potential targets. Active-learning methods [9] will be investigated, these architectures explicitly capable of supporting a human in the loop, reducing the burden on the analyst by guiding him/her to the most informative data, while also allowing the algorithms to adapt to new data, environments and missions. Submodular cost functions [10] will be investigated in the context of such active learning, yielding performance guarantees on algorithm performance and adaptivity. These methods will guide a human in the loop, and will also be used to optimally perform sensor management in complex, uncertain and evolving environments, defining experiments or courses of action for the autonomous agent.

The proposed team is highly experienced in working on Navy-relevant problems, and in the proposed program the research will be focused and the likelihood of transitions enhanced through close collaborations with Navy personnel. For example, the PIs have

long-term, ongoing and close collaborations with personnel from China Lake, that will be leveraged in the proposed effort. The PIs from UCLA and Duke will communicate regularly via email and Skype, with frequent visits among the PIs, students and post docs at the two institutions (*e.g.*, students from Duke will spend a semester at UCLA, and vice-versa).

1.2 Navy Relevance, Outcomes, and Impacts

The Navy must increasingly engage in unconventional warfare, addressing challenges of terrorism and counter-insurgency. In such missions accurate and timely interpretation of complex information is often the most powerful tool for the warfighter; this must be executed in the context of uncertain, incomplete, imprecise, and contradictory (UIIC) data. In such a setting it is essential to integrate conventional sensor data with unconventional information sources, many of which may be open-source, and are manifested in an unconventional “alphabet”. Specifically, unlike typical sensor data, unconventional information sources may be in the form of actual words. The problem is further complicated by the fact that the data are typically incomplete and contradictory, and inferences/actions must account for risks and sensing costs.

The proposed research seeks to address these challenges using a new class of mathematics and statistics, developed independently at UCLA and Duke, and to be integrated and unified within the proposed program. The proposed statistical methods from UCLA and Duke will be coupled (Profs. Bertozzi and Carin), and the performance will be improved using convex optimization techniques and convex splitting methods developed by Profs. Osher and Bertozzi. The principal products from the proposed research will be in the form of new mathematical and statistical models, which will be translated into algorithms and software. The software will be delivered to Navy collaborators, where it will be tested and refined based on relevant data. These collaborations will help sharpen and refine the research questions in the proposed research.

If successful, the proposed research has the potential to significantly advance the Navy’s ability to process complex, heterogeneous, and unconventional information sources. The proposed framework will markedly enhance the realism of models for handling complex information sources, moving beyond the assumption of simple Gaussian noise, addressing non-Gaussian (*e.g.*, spiky) noise and missing data. We will significantly advance a new class of models that build upon ideas in robust-PCA, allowing automatic detection of anomalies in general data, in the presence of significant missingness in the available data. As an example, we will integrate ideas from robust-PCA [3] and topic modeling [11], to statistically characterize the time evolution of the foreground and background in sophisticated video.

The proposed research is composed of three thrusts, each led by one of the investigators on the team. While these thrusts will be led by one of the investigators, all tasks and thrusts will be executed in concert, as a unified team. Further, we will work closely with Navy personnel, such as those at China Lake with whom we have a close and long-term relationship.

2 Technical Approach and Justification

We shall use recently discovered techniques in information science, machine learning and nonparametric Bayesian methods for developing robust representations, discovery of relationships and obtaining objectives from unstructured data. Then, we shall develop effective adaptive computational methods that have a capability to react to a dynamically changing picture, including feedback, with the goal of making good observations. These techniques include nonlocal means combined with machine learning, ℓ_1 related optimization and sparse reconstruction, dictionary learning and beta processes. These all address the issue of reconstruction and analysis of incomplete high dimensional data with possible contradictions and inaccuracies. Moreover, the Bayesian approach gives quantifiable probabilistic metrics. All these techniques will be combined to develop efficient, accurate, and flexible implementation strategies. To repeat: the PI's have a long and active history of collaboration with personnel from China Lake and other Navy laboratories. As a recent example, the turbulence data used in [12] came from China Lake.

2.1 Thrust I: Accurate Inference and Low-Dimensional Representations, leader S. Osher

Classification and Completion of Incomplete Information

In early work [13], Gilboa and Osher used a calculus from machine learning and weights from nonlocal means [14], somewhat localized, to do inpainting, which means filling in missing regions, classification and anomaly removal. This was done using nonlocal total variation and ℓ_1 type minimization. The anomaly removal in Fig. 2 was done without any prior knowledge and from using only a single image.

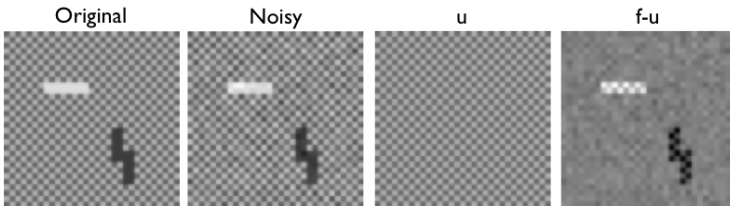


Figure 2: Removal of anomalies by nonlocal TV- ℓ_1 [13], which retains repetitive patterns and removes rare and irregular ones (light and dark symbols).

Clearly, having a video or multiple images can be very useful additional information. Merely stacking them vertically, missing data and all, gives us a matrix with missing entries. This has naturally led to an exciting area of research called Robust Principal Component Analysis [15]. Given a matrix which is the sum of a low-rank and a sparse component, it is possible to recover each of them exactly by measuring a weighted combination of all nuclear and ℓ_1 norms. This is true even if there are missing and/or corrupted elements. The method of choice for these algorithms seems to be augmented Lagrangian, which is exactly equivalent to split Bregman [16], in this case. This algorithm seems to be accurate and more robust than competitive approaches. At UCLA, members of our group [7, 17] have

developed a robust PCA algorithm for four dimensional computational tomography. This involves a spatiotemporal model regarded as a mixture of a low rank and sparse matrix. The low rank matrix corresponds to a stationary background, while the sparse matrix stands for moving or changing components. This work cleverly replaces the ℓ_1 term by a better regularizer. In [7], this group used tight framelets and in [17] (which did the decomposition for space/energy rather than space/time), they used total variation. This flexibility will give much better results for sparse components which are not spikes as happens with ℓ_1 , but have structure. Again, split Bregman gave reliable, accurate results. We are currently extending this to five dimensions, using space, time and energy. This decomposition already has given promising results in coded aperture snapshot spectral imagery. Simultaneously, co-PI Carin and collaborators have developed a different approach to the same problems based on a beta process approach, that leads to the construction of a dictionary which contains a good basis for the observed data. This basis can be used together with the variational robust PCA approach, where the regularization is not ℓ_1 , TV or framelets, but the ℓ_1 sum of these basis' coefficients or the associated nonlocal total variation based on these functions. This could be used in an iterative procedure, where we restore using a given dictionary and optimization, then improve the dictionary via this beta process, etc. Standard robust PCA involves an efficient convex optimization, but lacks an obvious probabilistic interpretation. The beta process updates the probability that particular models are consistent with data observations, but lacks a convex optimization interpretation. Combining these approaches will lead to advantages in robustness and accuracy.

A natural generalization of these approaches is to put nonlinearity into the low rank component. Some recent work done at UCLA [12] on blind restoration of a video of an image taken through a turbulent background has been quite successful using a model of the unknown image applied to an unknown random diffeomorphism. This could be incorporated, via splitting, in a robust PCA framework. Preliminary results are promising.

Improved Filtering for Dynamic Processing

Much of the UIIC data will come as a discrete time series. Just as ℓ_1 and TV regularization have improved solutions of inverse problems over quadratic regularizations, the same approach could be used to improve discrete-time and Kalman filters. With Russell Warren of EOstatinc, we have the following:

Our starting point is the discrete-time Kalman filter. We consider the linear evolution of the M -dimensional state vector x_k for $1 \leq k \leq N$ samples through the Markov model $x_k = \Phi x_{k-1} + q_k$, where Φ is the state transition matrix, and q_k are the plant noise variables modeled as independent, identically distributed (i.i.d.) normal random variable with mean zero and covariance Q . We assume that Φ and Q are known. The variables x_k are not observed directly, but through the measurement model $y_k = Ax_k + w_k$, where y_k are the K -dimensional data at time step k , A is a known $K \times M$ matrix, and w_k is the measurement noise vector assumed to be i.i.d. normal with mean zero and covariance matrix R .

The well-known discrete Kalman filter recursions for estimating x_k and its covariance P_k lead to simpler formulas for the variables $x_{k|k-1}$ and $P_{k|k-1}$, the model predictions of x_k and P_k given data up to time-step $k-1$, K_k is the Kalman gain matrix, and $x_{k|k}$ and

$P_{k|k}$ are the measurement update estimates using the new data y_k . The recursions are initialized by $x_{0|0}$ and $P_{0|0}$. Having the estimates of x_k and P_k , we can form the density of x_k conditional on the data up to time-step k , $Y_k \equiv \{y_j | 1 \leq j \leq k\}$:

$$f(x_k | Y_k) = \frac{1}{(2\pi)^{M/2} |P_{k|k}|^{1/2}} \exp \left[-\frac{1}{2} (x_k - x_{k|k})^T P_{k|k}^{-1} (x_k - x_{k|k}) \right].$$

This density (through its log-likelihood) forms the basis for adding the split Bregman regularization through an augmented Lagrangian approach.

More specifically, we define the augmented Lagrangian for time-step k :

$$L(x_k, d_k, b_k) = -\ln f(x_k | Y_k) + \|d_k\|_1 + \lambda \langle b_k, x_k - d_k \rangle + \frac{\lambda}{2} \|x_k - d_k\|_2^2,$$

and construct the saddle point estimates

$$(x_k^*, d_k^*, b_k^*) = \min_{x_k, d_k} \max_{b_k} L(x_k, d_k, b_k).$$

After substituting the definition of $f(x_k | Y_k)$, and differentiating with respect to x_k , we find at iteration l ,

$$x_k^{(l+1)} = (P_{k|k}^{-1} + \lambda I)^{-1} \left(P_{k|k}^{-1} x_{k|k} + \lambda (d_k^{(l)} - b_k^{(l)}) \right).$$

The corresponding updates to b and d are found by shrinkage and explicitly to be

$$d_k^{(l+1)} = S_\lambda \left(x_k^{(l+1)} + b_k^{(l)} \right), \quad b_k^{(l+1)} = b_k^{(l)} + x_k^{(l+1)} - d_k^{(l+1)}.$$

As a very simple example, we compared the standard Kalman, split Bregman, and combined Kalman/SB estimates on simulated time-series data constructed by adding white noise to a blurred two-spike model. The Kalman/SB procedure significantly outperformed the others. This idea could easily be extended to discontinuous time sequences using TV, rather than l_1 regularizations. In fact, more complicated dictionary based NLTV type regularizations, obtained, *e.g.*, from beta processes, could be used effectively. Results in [12] were improved by our colleague M. Micheli, using a Kalman filter together with optical flow and variational methods. We believe that combining this type of filtering with more sophisticated regularization is now tractable and will yield improved results for discontinuous data, received as a times-series, allowing efficient decision making.

Supervised Learning Method

Support vector machine (SVM), a classical supervised learning method that recognizes patterns and analyzes data, is widely used for classification and regression analysis. The standard SVM classifier is trained by quadratic programming (QP) with a combination of equality and inequality constraints [18]. An efficient SVM algorithm should not only be time-saving, but also keep the sparsity in support vectors, since later implementation requires processing of each new feature vector by matrices involving the entire training set.

Recently, inspired by the superior performance of the split Bregman method in ℓ_1 based minimization, we have derived a new efficient algorithm, split Bregman training of the

SVM classifier, for the above optimization problem. In order to test efficiency on high dimensional data, we designed numerical experiments and did some comparisons. For each N , we randomly generated a $N \times N$ positive definite matrix A as the input data, and recorded the time cost for both algorithms to solve for α . The difference between each pair of solutions is at most 10^{-7} in ℓ_1 norm. We ran the code 10 times and calculated the mean of the time displayed in Fig. 3.

	Size (N)	100	200	300	400	500	600
Time (sec)	QP	0.766	1.567	3.600	7.799	14.096	22.806
	SB	0.046	0.185	0.353	0.985	2.511	4.522

Figure 3: Comparison between algorithm (SB) and standard QP on simulated data.

Because of the above promising results and others, we believe our algorithm can deal with high dimensional data more effectively and accurately than conventional methods [18]. Our successful approach can be used for many unsupervised, semi-supervised and supervised models in machine learning besides SVM. The superior performance of split Bregman can help us build effective a priori recognition patterns for future data collection and the improved learning split Bregman approach has innumerable possible applications.

We now have several general procedures for solving problems related to SVM. In fact, any problem of the form $\min [\frac{1}{2}\alpha^T A\alpha - \alpha^T f]$, A is symmetric positive semidefinite, $\alpha = P(d)$, where P is a projection onto a convex set, can be solved with any of the following three new algorithms:

I *Split Bregman* (proven to converge for $\lambda > 0$)

Step 1: $d^{k+1} = P(\alpha^k - b^k)$;

Step 2: $\alpha^{k+1} = (\lambda A + I)^{-1}(\lambda f + P(d^{k+1}) + b^k)$;

Step 3: $b^{k+1} = b^k + P(d^{k+1}) - \alpha^{k+1}$.

II *Explicit projection* (proven to converge for $\lambda\|A\| < 2$).

$\alpha^{k+1} = P((1 - \lambda A)\alpha^k + \lambda f)$.

III *Implicit projection* (proven to converge for A positive definite)

Step 1: $d^{k+1} = d^k - 2(\alpha^k - P(\lambda f + 2\alpha^k - d^k))$;

Step 2: $\alpha^{k+1} = (\lambda A + I)^{-1}d^{k+1}$.

For example, with $A = B^T B$, we can solve the least squares problem: $\min \|Bu - g\|_2^2, u \geq 0$, for B tall and thin, much faster than current MATLAB routines. This is very useful for hyperspectral unmixing.

Anomaly and Target Detection

Osher and colleagues have worked on several projects that are related to the problem of anomaly detection. Although our previous work addressed different areas of hyperspectral imaging, including target detection, unmixing, endmember detection and image fusion, we believe that each of these projects contains some ideas that might be very useful for anomaly detection. In [8] a new hyperspectral target detection technique based on ℓ^1 regularization was proposed. Fig. 4 shows an example via ℓ^1 template matching: this is a hyperspectral image of a plant where two artificial leaves were added to the otherwise natural plant. Using the pixels in the boxes to perform target detection, our method detects the pixels marked in red as artificial. Despite the challenging data which is indistinguishable in the visible spectrum we were able to achieve a positive detection rate of 97.7%. The above method could be useful for anomaly detection: Besides being a reliable tool for identifying pixels similar to a certain target signature, one could use the template matching algorithm as a spectral clustering approach. For instance, starting with a random pixel as the targets signature, we find all pixels that are similar using the template matching algorithm. We remove all previously detected pixels from the image and repeat this procedure until no more pixel are left. As a result we obtain groups of spectrally similar pixels and can analyze the groups consisting of only very few pixels further with respect to the question if they are anomalies.

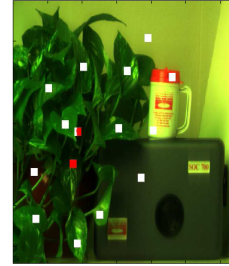


Figure 4: Target detection using ℓ_1 template matching.

2.2 Thrust II: Graphical and Fusion Methods and Temporal Data Analysis, leader A. Bertozzi

Multimodal Data Fusion

Bertozzi’s group has carried out focused efforts in multimodal datafusion resulting in new fused datasets that allow for inference of information not present in individual data. Two examples are discussed here. In [19, 20] we proposed a new method for fusing a low spatial resolution hyperspectral image with a high spatial resolution gray scale image, while preserving the spectral information. Figure 5 shows an example of such a fusion result. The left image is a high spatial resolution image we obtained as a screen shot from google maps. The middle image shows the same scene of the false color hyperspectral image. The spatial resolution of this image is too low to identify what the black spots on the white roof could be. After fusing the images, we can clearly see that there are some pipes on the roof and we have their spectral composition preserved.

This type of image fusion will be generalized to data coming from various types of sensors. Most likely, hybrid methods using as much spatial and spectral information as possible have the highest chances of producing robust anomaly detection results. In parallel, we will incorporate spatial information via TV minimization for anomaly detection. In [21] we consider the problem of estimating spatial probability densities from human event data. Fig. 6 shows spatially embedded human event activity and how additional information



Figure 5: Hyperspectral image fusion from [19]. Left image from Google maps, middle image is hyperspectral AVIRIS data. Fused image on right (false color).

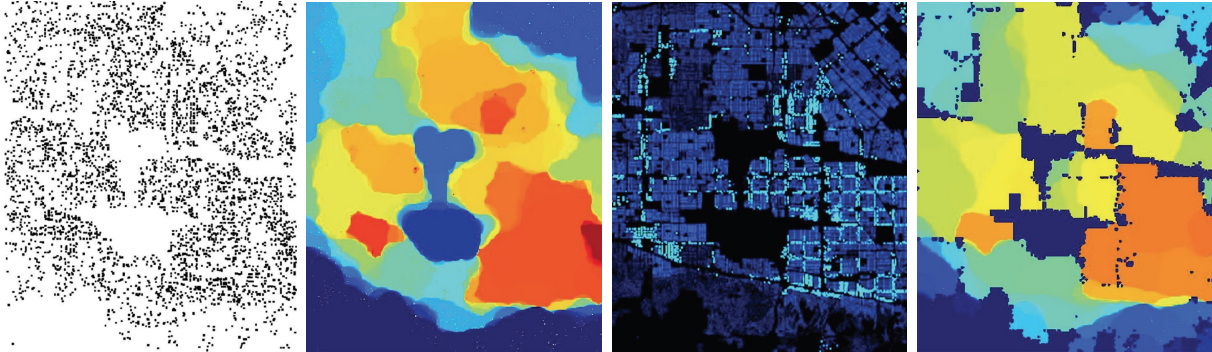


Figure 6: From left to right: (1) locations of 4,487 residential burglaries in an 18×18 km area of the San Fernando Valley during 2004-2005; (2) maximum penalized likelihood estimation of the crime density using fast TV regularization [22]; (3) residential housing density for the same region; (4) Modified MPLE method including edge information from (3) [21].

such as residential housing density can provide more accuracy. These examples show how to combine various modalities including spectral, spatial, and human activity however they do not include temporal data. One challenge that this project will address is data fusion across space and time and the ability of datafusion algorithms to aid in identification of real time anomaly detection in complex and incomplete datasets combining with ideas from Osher’s work and with Bayesian methods in collaboration with Carin.

Graph Based Methods

Bertozzi and Arjuna Flenner (China Lake) have developed computational algorithms for classification of incomplete information in a general graph-based framework [23]. The method applies to very diverse datasets not just those involving spatial and spectral information such as high dimensional imagery. For example we have successfully applied the method to classify party affiliation in the US Congress based on voting records. The algorithm is related to L1-TV approaches and is built around the classical Ginzburg-Landau functional, a diffuse interface approximation of the TV functional, originally derived for physical sciences problems such as phase transition. Diffuse interface models in Euclidean

space are often built around the Ginzburg-Landau functional

$$GL(u) = \frac{\epsilon}{2} \int |\nabla u|^2 dx + \frac{1}{\epsilon} \int W(u) dx$$

where W is a double well potential. For example $W(u) = (u^2 - 1)^2$ in the case where W has minimizers at plus and minus one. There are several interesting features of GL minimizers. For example, the transition region between the two phases typically has some length associated with it and the GL functional is roughly proportional to this length. This can be made rigorous by considering the notion of Gamma convergence of the Ginzburg-Landau functional. It is known to converge [24] to the total variation semi-norm,

$$GL(u) \rightarrow_{\Gamma} C|u|_{TV}.$$

The Ginzburg-Landau functional is used in image processing as an alternative or a relative to the TV semi-norm. Non-binary data (such as grayscale imagery) can be efficiently dealt with using a binary bitwise representation of the data and treating each bit separately [25]. In a typical application we minimize an energy functional of the form

$$E(u) = GL(u) + \lambda F(u, d)$$

where different $F(u, d)$ terms correspond to different imaging tasks. The energy $E(u)$ can be minimized in the L^2 sense using a gradient descent, which gives us a modified Allen-Cahn equation

$$u_t = -\frac{\delta GL}{\delta u} - \lambda \frac{\delta F}{\delta u} = \epsilon \Delta u - \frac{1}{\epsilon} W'(u) - \lambda \frac{\delta F}{\delta u}.$$

This can be evolved to steady state to obtain a local minimizer of the energy E .

Convex splitting schemes are based on the idea that an energy functional can be written as the sum of convex and concave parts, $E(u) = E_{vex}(u) - E_{cave}(u)$ where this decomposition is not unique because we can add and subtract any convex function and not change E but certainly change the convex/concave splitting. When combined with gradient descent, we perform a time stepping scheme in which the convex part is done implicitly and the concave part explicitly:

$$\frac{u^{n+1} - u^n}{dt} = -\frac{\delta E_{vex}}{\delta u}(u^{n+1}) + \frac{\delta E_{cave}}{\delta u}(u^n). \quad (1)$$

The art then lies in choosing the splitting so that the resulting scheme is stable and also computationally efficient to solve. This method was popularized by a well-known but unpublished manuscript by David Eyre [26] and has been successfully used in [27, 28, 25]. This same idea has also been directly discussed in the context of general minimization procedures for nonconvex functionals [29].

One can consider a generalization of the GL functional to Graphs. This will be in the same spirit as the work [25] generalizing the GL functional to wavelets. We now describe how to generalize the Ginzburg Landau functional, or more precisely its L^2 gradient flow, to the case of functions defined on graphs [30]. One challenge is the normalization of the Laplacian due to the fact that we are working with purely discrete functionals that may not have a direct spatial embedding. Consider an undirected graph $G = (V, E)$ with vertex

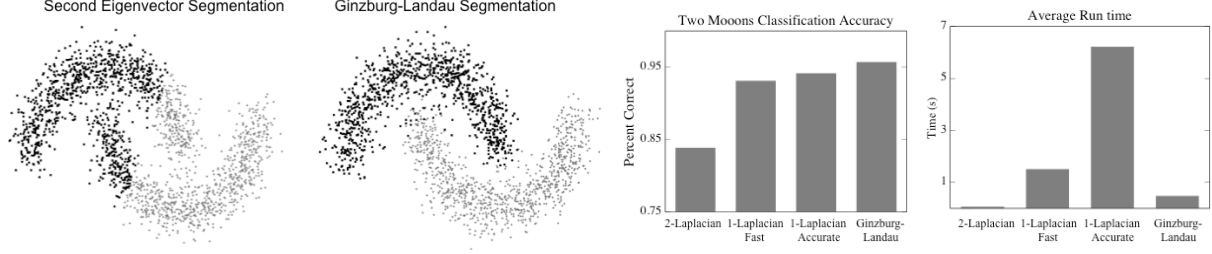


Figure 7: (left) Two moon dataset embedded in R^{100} , segmented via second eigenvector of the graph Laplacian vs. the Ginzburg-Landau functional [23]; (right) Performance comparison for GL-minimization vs. recent 2-Laplacian and 1-Laplacian methods.

set $V = \{v_1, \dots, v_N\}$ and edge set E . The edge set of an unweighted graph can be defined from a binary weight function $w(v, u)$ where

$$w(v, u) = \begin{cases} 1 & \text{if there exists an edge joining vertex } v \text{ and vertex } u \text{ with } v, u \in V, \\ 0 & \text{if no edge exists joining } v \text{ and } u \text{ with } v, u \in V. \end{cases} \quad (2)$$

The degree of a vertex $v \in V$ is defined as $d(v) = \sum_{u \in V} w(v, u)$. Note that, by the definition of $w(v, u)$, $d(v)$ simply counts the number of connections between two elements u, v in the vertex set V . The degree matrix D can then be defined as the $N \times N$ diagonal matrix with diagonal elements $d(v)$. Define the graph Laplacian $L(u, v)$ as

$$L(u, v) = \begin{cases} d(u) & \text{if } u = v, \\ -w(u, v) & \text{otherwise} \end{cases} \quad (3)$$

it can be written in matrix form as $L = D - W$ where W is the matrix $w(u, v)$. The above construction easily generalizes to weighted graphs. A weighted undirected graph [30] has an associated weight function $w : V \times V \rightarrow R$ satisfying $w(u, v) = w(v, u)$ and $w(u, v) \geq 0$. The definition for the degree of the vertex $d(v)$ and the volume of a subset A , $vol(A)$, and the graph Laplacian are the same as the unweighted graph [30, 31]. In [23] we use the symmetric Laplacian L_s defined as

$$L_s = D^{-1/2} L D^{-1/2} = I - D^{-1/2} W D^{-1/2}. \quad (4)$$

The symmetric Laplacian is named as such since it is a symmetric matrix. The random walk Laplacian is another important normalization and arises in recent work on nonlocal means functionals [32, 13, 14]. One can extend the Ginzburg-Landau energy to graphs by minimizing the following [23]

$$\epsilon < L_s u, u > + \left(\frac{1}{\epsilon}\right) \sum W(u) + \sum \lambda(x)(u - u_0)^2, \quad (5)$$

where the sum is over all nodes on a graph and the L_s is defined above. The last term in the energy is a fidelity term that represents known information on part of the image specified by the characteristic function lambda. The method minimization is performed

quickly using a combination of a convex splitting algorithm and fast linear algebra routines for computing the eigenvectors and eigenfunctions of the graph Laplacian. An example with high dimensional abstract data is shown in Fig. 7. In another example we are able to predict with over 95% accuracy, the party affiliation of all members of the US House of Representatives based on known affiliation of just 5 members and voting records for 16 votes in 1984. In a third example (Fig. 8) we consider an image of cows in which the animals are (inaccurately) hand labeled in the first image and automatically identified in the second image. This last example uses non-local means weights for the graph Laplacian in which the entire weighted graph is fully connected. This results in a computationally expensive linear algebra problem that can be done efficiently using Nyström extension methods [33]. The results are more efficient than traditional TV-NL means methods with similar results.

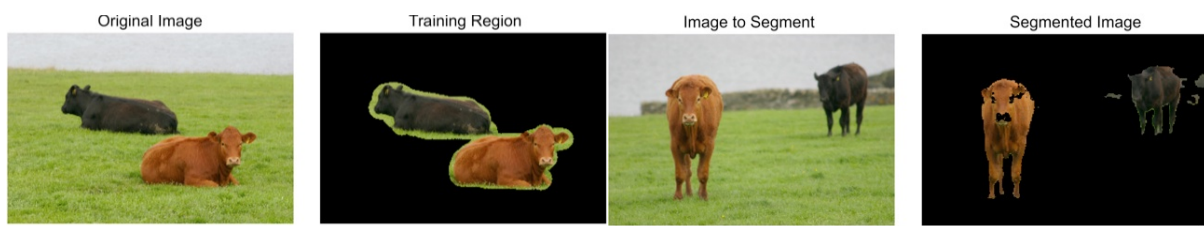


Figure 8: In this machine learning example, cows are roughly segmented by hand in the first image and automatically identified in the second image [23].

Temporal signatures in complex data

Bertozzi’s group has also been active in developing models for temporal signatures in complex datasets. There are two classes of examples they have worked with: change point detection filters and self exciting point process models.

Change point detection methods are used for real time decisions based on noisy datasets when the question of interest is to identify a change of state with a low false alarm rate and low average detection delay. Her group has applied cumulative sum filters [34, 35] to specific problems such as robotic path planning based on noisy sensor information for tasks such as obstacle avoidance in real time [36] and cooperative boundary tracking [37, 38]. The latter idea has been extended to the design of algorithms for boundary tracking in large image datasets [39] and has led to a CDI grant from the NSF for the design of real-time algorithms for atomic force microscopy in collaboration with Lawrence Berkeley National Lab. The CUSUM filter applied to time series data is the optimal method for detecting sharp jumps, in contrast to the Kalman filter which assumes a linear change of state. As an analogy to variational methods for spatial data, the Kalman filter is the analogue of the Wiener filter whereas the CUSUM filter would be analogous to total variation minimization. It would be interesting to explore the design of new algorithms based on these different filtering techniques in applications of interest to this project.

Self-exciting point process models are well-known for modeling aftershocks in earthquake data. Very recently they have provided significant insight into tracking and

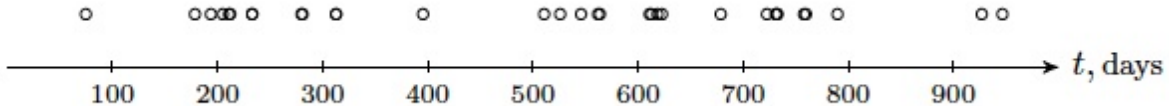


Figure 9: Temporal clustering of the interaction events between Clover and East Lake gangs in Los Angeles, during the period 1999-2002.

modeling human activity that is not entirely random in time. Some examples from the literature include domestic crime such as burglaries and robberies [40], more organized crime such as gang retaliation [41, 42], and very recently the study of IED activity in Iraq [43]. Fig. 9 shows known temporal activity between a pair of rival gangs in the Hollenbeck division of the Los Angeles Police Department, during the period 1999-2002. Note the clustering of events in time. This type of data, for which many of the activities are known to be retaliatory and thus not random, can be modeled by a Hawkes process [44, 45] $\lambda(t) = \mu + \theta \sum_{t_i < t} \omega e^{-\omega(t-t_i)}$ where μ is the background rate of events in the absence of self-excitation, ω^{-1} sets the timescale over which the overall rate $\lambda(t)$ returns to its basely level after an event occurs. From the behavioral point of view, θ represents the average number of direct offspring for each event and ω^{-1} is the expected waiting time until an offspring. In our recent work [41] we have used this model to develop an algorithm for filling in missing information from a network of gang crimes. An open problem is to develop filtering techniques to accurately distinguish between excitation events and background events. Such problems are of high importance in accurately predicting adversarial behavior.

2.3 Thrust III: Nonparametric Bayes, Heterogeneous Data and Value of Information, leader L. Carin

There has been much recent interest in developing statistical models for automatic clustering and annotation of images, based on local image features as well as available meta-data such as image annotations [46, 47, 48, 49, 50, 51, 52, 53]. Such models constitute a natural way to jointly analyze heterogeneous data with distinct alphabets (here images and documents, but the statistical methods are general). In the proposed research we will develop these models and the underlying theory, for general heterogeneous data, and make connections to optimization-based approaches that will be the focus of other team members (Prof. Bertozzi). Below we discuss the problem of joint analysis of imagery and documents (*e.g.*, HUMINT), to make the discussion concrete.

Statistical topic models, such as probabilistic Latent Semantic Analysis (pLSA) [54] and Latent Dirichlet Allocation (LDA) [55], originally developed for text analysis, have been successfully applied for these image-analysis tasks by representing an image as a bag of visual words [47]. Local image descriptors, *e.g.*, scale-invariant feature transform (SIFT) [56], are commonly used to extract features from local patches, segments, or super-pixels [52]. The extracted local features are used to design a discrete codebook (*i.e.*, vocabulary) with vector quantization (VQ). When analyzing images, each local descriptor

is subsequently assigned to one of the codewords [47, 51, 52], with these codes playing the role of discrete words in traditional documents. Although significant success has been achieved with this approach, there is no principled way to define the codebook size, and hence this parameter must be tuned and is in general a function of the dataset considered. Further, the feature extraction (*e.g.*, via SIFT) is performed separately from the subsequent statistical analysis, making it unclear which features should be used and why one class of features should be preferred.

Recent research on dictionary learning and sparse coding has demonstrated superior performance in a number of challenging image processing applications, including image denoising, inpainting and sparse image modeling [57, 58, 59]. Recent advances in image classification show that substantially improved performance may be achieved by extracting features from local descriptors with dictionary learning and sparse coding, this replacing VQ [60, 61]. However, it is not clear how to integrate these tools with topic modeling, to constitute an overall statistical model.

In the discussion below we propose a novel Bayesian model that integrates dictionary learning, sparse coding and topic modeling, for joint analysis of multiple images and (when present) associated annotations (which plays the role of HUMINT). The model links topics to probabilities for use of particular dictionary elements, with the dictionary learned jointly while performing topic modeling. The learned model clusters all images into groups, based upon dictionary usage, and a statistical distribution is also provided for words that may be associated with previously non-annotated images (only a subset of the images are assumed annotated when learning the model). Below we develop the modeling framework and explain how inference is performed; preliminary results from the analysis are demonstrated on common databases, with comparisons to previous research on similar problems.

Review of Bayesian Dictionary Learning and Topic Modeling

Let $\mathbf{x}_i \in \mathbb{R}^P$ represent the i th data sample and $\{\mathbf{x}_i\}_{i=1,N}$ represents the complete data set under analysis. For the application considered here, each \mathbf{x}_i corresponds to a set of contiguous pixels (from a small image “patch” extracted from an overall image). The set $\{\mathbf{x}_i\}_{i=1,N}$ represents data extracted from N image patches, across all images of interest. Each \mathbf{x}_i is represented as a linear combination of a sparse set of atoms from a dictionary $\mathbf{D} \in \mathbb{R}^{P \times K}$, where the columns of \mathbf{D} represent dictionary atoms. A prior is placed on \mathbf{D} , and a posterior density function on \mathbf{D} is learned based on $\{\mathbf{x}_i\}_{i=1,N}$. Further, the size of the dictionary (total number of *active* atoms across all \mathbf{x}_i) is unknown, and to be inferred; *i.e.*, it is anticipated that only a subset of the K dictionary elements are used. Specifically, for each i , $\mathbf{x}_i = \mathbf{D}\boldsymbol{\alpha}_i + \boldsymbol{\epsilon}_i$, where $\boldsymbol{\alpha}_i \in \mathbb{R}^K$ is sparse and $\|\boldsymbol{\epsilon}_i\|_2/\|\mathbf{x}_i\|_2 \ll 1$. Additionally, a prior is placed on $\{\boldsymbol{\epsilon}_i\}_{i=1,N}$, and the statistics of the residual are also to be inferred.

In recent research [59], it has been demonstrated that the beta process (BP) and Bernoulli process (BeP) may be coupled to constitute a prior on $\{\boldsymbol{\alpha}_i\}_{i=1,N}$ and \mathbf{D} , to impose the desired sparseness and to infer the dictionary composition and size; this construction also imposes that many of the \mathbf{x}_i will use a similar subset of columns of \mathbf{D} . In the model developed below, we consider analysis of multiple images simultaneously. Each image is drawn from a distribution over topics, and therefore each image is associated with

one topic. Each topic is characterized by a distribution over object types that may occur in the image, and in the absence of annotations the number of object types is inferred via the images alone. When annotations are available, the number of objects is linked with the total number of unique words across all annotations. To link the topic model to dictionary learning, each object type will have an associated probability of using columns of \mathbf{D} , and therefore each object type places a prior on the sparseness of the coefficients α_i . In this manner, topic modeling and dictionary/feature learning may be performed jointly.

Bayesian Hierarchical Model

Given a set of M images, we represent each image as a set of local patches. The m th image is represented as $\{\mathbf{x}_{mi}\}_{i=1, N_m}$, where N_m represents the total number of patches in this image, and \mathbf{x}_{mi} is the data from the i th patch. We use Bayesian dictionary learning on the data $\{\mathbf{x}_{mi}\}_{m=1, M; i=1, N_m}$ to infer a dictionary \mathbf{D} under which each \mathbf{x}_{mi} is sparsely represented. Specifically, each \mathbf{x}_{mi} is represented as $\mathbf{x}_{mi} = \mathbf{D}(\mathbf{z}_{mi} \odot \mathbf{s}_{mi}) + \epsilon_{mi}$ where \odot represents the pointwise/Hadamard vector product, K is the truncation level on the possible number of dictionary atoms, $\mathbf{z}_{mi} = [z_{mi1}, \dots, z_{miK}]^T$, $\mathbf{s}_{mi} = [s_{mi1}, \dots, s_{miK}]^T$, $z_{mik} \in \{0, 1\}$ indicates whether the k th atom is *active* within patch i in image m , $s_{mik} \in \mathbb{R}$, and ϵ_{mi} is the residual error. Note that under an appropriate dictionary \mathbf{D} , \mathbf{z}_{mi} represents the specific sparseness pattern of dictionary usage for \mathbf{x}_{mi} . This part of the model is as in previous Bayesian dictionary learning [59], and the unique component of the model is to link the sparse binary vector \mathbf{z}_{mi} to a topic model. We assume that each image is associated with a topic (scene class). Each topic is in turn characterized by a distribution over objects. Finally, each object is characterized by a distribution on the usage of particular dictionary elements.

Let $r_m \in \{1, \dots, T\}$ indicate the topic (scene type) the m th image is associated with; this random variable is assumed drawn from a multinomial distribution $\boldsymbol{\mu} = (\mu_1, \dots, \mu_T)^T$ with a uniform Dirichlet prior as

$$r_m \sim \sum_{t=1}^T \mu_t \delta_t, \quad \boldsymbol{\mu} \sim \text{Dir}(\alpha_\mu/T, \dots, \alpha_\mu/T), \quad (6)$$

where δ_t is a unit measure at the point t . Each topic is characterized by a distribution over object types, with a maximum of J object types assumed. The probability vector $\boldsymbol{\nu}_t \sim \text{Dir}(\alpha_\nu/J, \dots, \alpha_\nu/J)$ defines the probability that each of the J objects is observed in topic $t \in \{1, \dots, T\}$. Hence, if topic $r_m \in \{1, \dots, T\}$ is associated with image $m \in \{1, \dots, M\}$, then the objects associated with image m are drawn from $\boldsymbol{\nu}_{r_m}$. Let $h_{mi} \sim \sum_{j=1}^J \nu_{r_m j} \delta_j$ represent an indicator variable defining which of the J objects is associated with patch i in image m .

We now place a probability distribution on use of dictionary elements (columns of \mathbf{D}) that is linked to which object a given patch is associated with. Hence, for each object type, we define a probability over usage of the K potential dictionary elements (columns of \mathbf{D}). Specifically, the vector $\boldsymbol{\pi}_j$ defines the probability that each of the K columns of \mathbf{D} is employed to represent object type $j \in \{1, \dots, J\}$, where the k th component of $\boldsymbol{\pi}_j$ is a probability satisfying $\pi_{jk} \in (0, 1)$, $k \in \{1, \dots, K\}$. This K -dimensional vector of probabilities is defined as $\boldsymbol{\pi}_j \sim \prod_{k=1}^K \text{Beta}(c_0 \eta_0, c_0(1 - \eta_0))$. Then as in conventional dictionary learning

[59], the binary vector $\mathbf{z}_{mi} \sim \prod_{k=1}^K \text{Bernoulli}(\pi_{h_{mi}k})$ defines which dictionary elements are used for representation of \mathbf{x}_{mi} . Summarizing, for the m th image, we first draw a topic r_m . Then, for each patch i in image m we draw an object type $h_{mi} \sim \text{Mult}\{\boldsymbol{\nu}_{r_m}\}$. Finally, for this object type there is an associated probability vector of Bernoulli inputs $\boldsymbol{\pi}_{h_{mi}}$, from which the binary vector \mathbf{z}_{mi} is drawn, defining which columns of \mathbf{D} are used for representation of the data in patch i of image m , \mathbf{x}_{mi} . If annotations are available for at least a subset of the M images, it is desirable to leverage this information. When available, the words associated with image m are represented as $\mathbf{y}_m = (y_{m1}, \dots, y_{mJ})$, where y_{mj} denotes the number of times word j is present in the annotation to image m . Typically, y_{mj} will be either one or zero. Since the number of words in the annotation $|\mathbf{y}_m|$ may be very different than the number of patches N_m , we scale \mathbf{y}_m such that the words and image features contribute comparably within the likelihood function. Specifically, we perform the scaling $\mathbf{y}'_m = (N_m/|\mathbf{y}_m|)\mathbf{y}_m$, where in each component of \mathbf{y}'_m we take the nearest non-negative integer. This scaled annotation count is assumed drawn as $\mathbf{y}'_m \sim \text{Mult}(\boldsymbol{\nu}_{r_m}, N_m)$ such that the topic-dependent draw of words in the annotation is consistent with the associated draw of patch-dependent objects within the image. Fig. 10 shows a diagram of the proposed model, where shaded and unshaded nodes indicate observed and latent variables, respectively. An array indicates dependence between variables. The boxes are plates that denote repetition, with the number of repetitions indicated by the variables in the corner of boxes.

Summary of Model Inference

Because each consecutive layer in the hierarchical model is in the conjugate-exponential family, efficient Gibbs sampling inference can be used. The inference equations for the dictionary \mathbf{D} , the binary sparse codes \mathbf{z} and the real sparse codes \mathbf{s} are similar to that in [59], and are omitted for brevity. Below we briefly summarize update equations for unique aspects of the proposed model:

Sampling $\boldsymbol{\pi}_j$: the dictionary usage for object j is sampled from a beta distribution as: $p(\boldsymbol{\pi}_j | -) \sim \text{Beta}(a_j, b_j)$ where $a_j = a_0 + \sum_{m=1}^M \sum_{i=1}^{N_m} \delta(h_{mi} = j) \mathbf{z}_{mi}$, and $b_j = b_0 + \sum_{m=1}^M \sum_{i=1}^{N_m} \delta(h_{mi} = j) (1 - \mathbf{z}_{mi})$.

Sampling r_m : the scene category topic indicator r_m is sampled from a T -dimensional multinomial distribution as:

$$p(r_m = t | -) \propto \mu_t \prod_{j=1}^J \nu_{tj}^{y'_{mj} + \sum_{i=1}^{N_m} \delta(h_{mi}=j)}. \quad (7)$$

Sampling h_{mi} : the object indicator h_{mi} is sampled from a J -dimensional multinomial

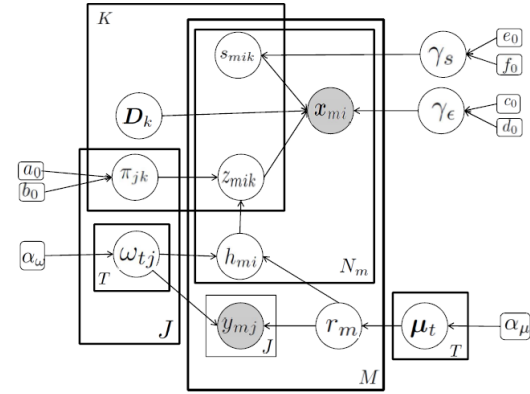


Figure 10: Graphical representation of the model.

distribution as:

$$p(h_{mi} = j | -) \propto \nu_{r_{mj}} \prod_{k=1}^K \pi_{jk}^{z_{mik}} (1 - \pi_{jk})^{1 - z_{mik}}. \quad (8)$$

Sampling ν_{tj} and μ_t :

$$p(\nu_{tj} | -) \sim \text{Dir}(\nu_{t1}^*, \dots, \nu_{tJ}^*) \quad p(\mu_t | -) \sim \text{Dir}(\mu_1^*, \dots, \mu_T^*)$$

where $\nu_{tj}^* = \frac{\alpha_\nu}{L} + \sum_{m=1}^M [y'_{mj} + \sum_{i=1}^{N_m} \delta(h_{mi} = j)] \delta(r_m = t)$ and $\mu_t^* = \frac{\alpha_\mu}{T} + \sum_{m=1}^M \delta(r_m = t)$.

We first test the model using the MNIST handwritten digit database, considering 50 samples per digit (digits 0 through 9), thus $N = 500$ in total. We randomly select 50 partially overlapping patches per digit, and each patch is of size 15×15 (the original digit images are of size 28×28). All the patches are used to constitute the data matrix $\mathbf{X} \in \mathbb{R}^{P \times N}$, where $P = 225$ and $N = 25,000$. The matrix \mathbf{X} is pre-whitened with principal component analysis (PCA) and the first $L = 100$ principle components are preserved as features ($L = 100$ keeps about 95% energy of the original data, achieves a good balance between accuracy and complexity). We set truncation levels as $K = 200$, $J = 50$ and $T = 20$; these are upper bounds

on the associated parameter, while the model infers the number of components needed. The inferred dictionary atoms are shown in Fig. 11 in order of importance. For some runs, the proposed model infers more than 10 non-zero topic weights, *i.e.*, some digits such as 4 and 5 tend to occupy more than one topic and there may be a total of 12 topics inferred. In order to draw a confusion matrix, multiple topics of the same digit are combined according to the ground truth. The average confusion matrix is calculated in Fig. 12 with the average performance 80.4%. This performance is achieved with an *unsupervised* model.

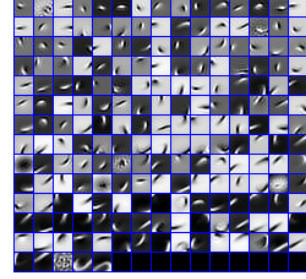


Figure 11: The inferred dictionary for the MNIST digit data.

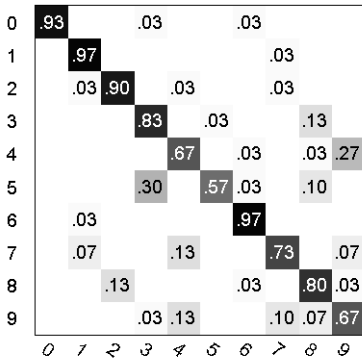


Figure 12: Confusion matrix for the MNIST digit data. The value for a blank parts is zero.

For the MSRC data (from Microsoft Research), we choose 320 images from 10 categories of images with manual annotations. The categories are “tree”, “building”, “cow”, “face”, “car”, “sheep”, “flower”, “sign”, “book” and “chair”. There are respectively 45 and 35 images in the “cow” and “sheep” classes, and 30 in all the other classes (here the category is expected to be associated with a topic in our model). Each image has size 213×320 or 320×213 . We evenly divide each (color) image into $32 \times 32 \times 3$ non-overlapping patches. Similarly to the experiment setting for the MNIST digit data set, we choose $L = 100$, $K = 200$ and $T = 20$. No parameter optimization has been performed. For annotations, we remove all annotation-words that occur less than 8 times (approximately 1% of them). There are 15 unique annotation-words: “building”, “grass”, “tree”,

“cow”, “sheep”, “sky”, “water”, “face”, “car”, “flower”, “sign”, “book”, “chair”, “road” and “people”. For each category, we randomly choose 10 images, and remove their annotations, treating them as non-annotated images within the analysis (to allow quantification of inferred-annotation quality). We assume that each annotation word corresponds to a visual object in the image, thus $J = 15$. With these data we typically infer 14 topics (there are actually 10 scene types from which the images are constituted). We use the same method as in the MNIST experiment to integrate multiple inferred topics/scenes, to compute a confusion matrix. The average performance is 86.8%, outperforming the results in [52] by 3.9% under the same test settings.

Based on the learned posterior word distribution ν_t for the t th scene class, we can further infer which objects are most probable for each scene class (topic). Figure 13 shows the ν_t for 9 classes, with the largest five probabilities displayed, a good connection is manifested between the words and image types.

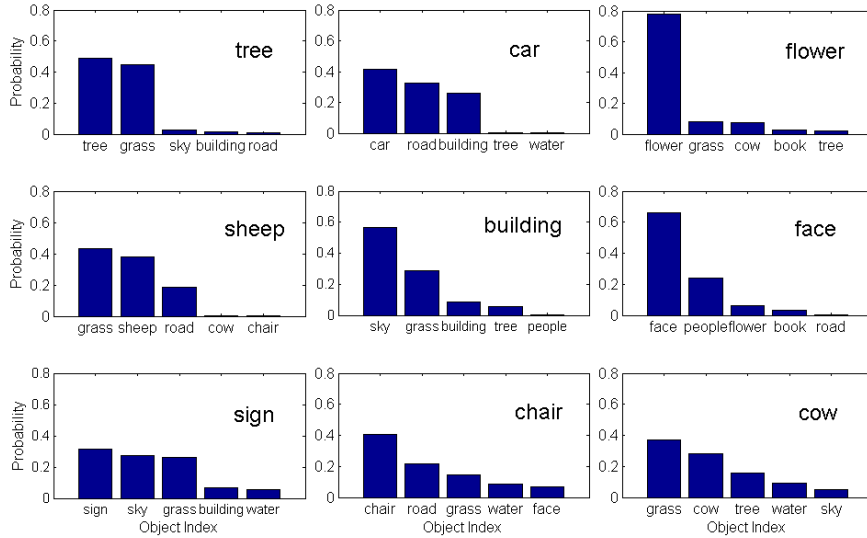


Figure 13: Each topic is characterized by a distribution over objects, and these objects may be linked to words via the annotation, when available. For the MSRC data we display the word probabilities for inferred topics. We may therefore connect words to the topics, with the first row reflecting “tree”, “car” and “flower” topics, for example.

6. Value of Information

An important aspect of the proposed program involves adaptive collection of data, to remove uncertainties and mitigate contradictory data. The statistical models discussed above naturally yield measures of confidence in each inference, as quantified in terms of the posterior density function. These statistical measures will be used within the proposed research to quantify the value of new data acquisitions, accounting for acquisition costs, within a risk-based construction. New ideas from submodular theory will be employed to yield performance guarantees on the overall system performance.

3 Project Schedule and Milestones

Below we give a detailed summary of the tasks to be undertaken in the proposed program. For each task we list the anticipated execution time, as well as the investigator taking the lead responsibility. Within the proposed program the three investigators will act as an integrated team, with frequent communication, and visits to the two institutions by the PIs and associated graduate students and post docs. All investigators on the team are highly experienced, and therefore the management overhead is anticipated to be minimal. A key component of the proposed research, anticipated by close interaction between the investigators, is to yield a unifying theory around the optimization and Bayesian statistical and mathematical tools proposed here.

3.1 Year 1 Tasks

Task 1A: Development of graphical methods for timeseries data

Lead: Bertozzi; time period: 6 months

Task 1B: Data fusion methods combining with Bayesian dictionaries

Lead: Bertozzi; time period: 6 months; collaborating lead: Carin

Task 1C: Nonparametric-Bayesian analysis of heterogeneous space-time data

Lead: Carin; time period: 7 months

Task 1D: Incorporation of graphical priors in Bayesian analysis

Lead: Carin; time period: 5 months; collaborating lead: Bertozzi

3.2 Year 2 Tasks

Task 2A: Variational robust PCA using improved regularization with the help of beta processes

Lead: Osher; time period: 6 months; collaborating lead: Carin

Task 2B: Combine variational robust PCA with beta processes using an iterative procedure

Lead: Osher; time period: 6 months; collaborating lead: Carin

Task 2C: Temporal modeling of timeseries data embedded in high dimensional graphs

Lead: Bertozzi; time period: 6 months

Task 2D: Concept Drift and Model Refinement Over Time

Lead: Carin; time period: 6 months

3.3 Year 3 Tasks

Task 3A: Value of Information & Submodularity

Lead: Carin; time period: 6 months

Task 3B: Information value as timeseries data

Lead: Bertozzi; time period: 6 months; collaborating lead: Carin

Task 3C: Include nonlinear effects in the low rank components of this combined sparse/low rank decomposition

Lead: Osher; time period: 6 months

Task 3D: Improve Kalman and other time series filtering via modern regularization techniques

Lead: Osher; time period: 6 months; collaborating lead: Bertozzi

3.4 Year 4 Tasks

Task 4A: Improve support vector machine and other learning methods via split Bregman and projection methods

Lead: Osher; time period: 6 months

Task 4B: Prediction of self-excitation in adversarial data

Lead: Bertozzi; time period: 6 months; collaborating lead: Carin

Task 4C: Online Learning and Very-High-Dimensional Data Sets

Lead: Carin; time period: 6 months; collaborating lead: Bertozzi

3.5 Year 5 Tasks

Task 5A: Variational Bayesian Analysis and Fast Optimization

Lead: Carin; time period: 6 months; collaborating lead: Osher

Task 5B: Generalize our anomaly detection and related classification and detection techniques by hybrid methods combining various types of sensor data

Lead: Osher; time period: 6 months; collaborating lead: Bertozzi

Task 5C: Efficient convex splitting methods for graphical time series data
Lead: Bertozzi; time period: 6 months

4 Management Approach

The Principal Investigator is Professor Stanley Osher of UCLA's Mathematics, Computer Science, Electrical Engineering Departments and its NSF funded Institute for Pure and Applied Mathematics, who will assume all responsibilities for the program. However the PI and the two co-PIs, Professor Andrea Bertozzi, of UCLA's Mathematics Department and Professor Lawrence Carin of Duke University's Electrical and Computer Engineering Department, will form an executive committee to oversee the scientific direction and allocation of resources. The PI will interface directly with ONR, but scientific and administrative decisions will be made democratically by the executive committee.

The team members' expertise in complementary and overlapping areas, as described in the technical approach and summarized in Fig. 1 will lead to continuous interaction with the tasks listed below steering us towards desired milestones.

The UCLA team will meet biweekly together with students and postdocs to report on progress and Professor Carin will teleconference in. He will also visit the UCLA team three times per year. These visits will be timed to include, whenever possible, Navy personnel from China Lake.

We intend to freely distribute all of our results, both codes and reports obtained in this effort to Navy personnel. We will also encourage the Institute for Pure and Applied Mathematics at UCLA to run short workshops with other participants in this program.

5 Qualifications

5.1 Stanley J. Osher (sjo@math.ucla.edu)

University of California at Los Angeles
Department of Mathematics
Los Angeles, CA 90095-1555
Tel: 310-825-1758

Professional Preparation

Brooklyn College Physics B.S. 1962
New York University Mathematics M.S. 1964
New York University Mathematics Ph.D. 1966

Appointments

1977-Present Professor, UCLA, Department of Mathematics
1975-1977 Professor, SUNY, Stony Brook, 1975-77
1970-1975 Associate Professor, SUNY, Stony Brook
1968-1970 Assistant Professor, University of California Berkeley
1966-1968 Assistant-Associate Mathematician, Brookhaven National Laboratories

Synergistic Activities

1. Coinventor and a principle developer of i) state-of-the-art high resolution schemes for hyperbolic conservation laws and Hamilton-Jacobi equations; ii) level set methods for moving fronts involving topological changes iii) total variation and other partial differential equations based image processing techniques, iv) fast algorithms for L1 type optimization. His work has been in the scientific and international media, e.g. science News, Die Zeit.
2. He has had approximately 60 invited lectures in the past two years.
3. He is or was recently associate editor of 11 journals.
4. He was co-organizer of several long meetings at the NSF-funded Institute for Pure and Applied Mathematics (IPAM) at UCLA.
5. He is Director of Special Projects at IPAM and has a joint faculty appointment with UCLAs Electrical Engineering and Computer Science Departments.
6. He has co-founded three successful companies, each based largely on his own research.
7. He has graduated over 50 Phd students and mentored over 45 postdoctoral fellows.

Achievements and Honors Fulbright Fellow, 1971 Alfred P. Sloan Fellow, 1972-1974 SERC Fellowship (England), 1982 US-Israel BSF Fellow, 1986 NASA Public Service Group Ach. Award, 1992 Invited speaker, Int. Cong. Math., Zurich, 1994, ICI Original Highly Cited Researcher, 2002, Japan Soc. of Mech. Eng., Comp. Mech. Award (2002), ICIAM Pioneer Prize, 2003, Elected to US Nat. Acad. of Sci., 2005, SIAM Ralph E. Kleinman Prize, 2005, Docteur Honoris Causa, ENS Cachan, France 2006 US Ass. for Comp. Mech. Comp. and Appl. Sci. Award, 2007, SIAM Fellow 2009, Elected to the Am. Acad. of Arts and Sci., 2009, Honorary Doctoral Degree Hong Kong Baptist University 2009, SIAM Fellow 2009, plenary speaker Int. Cong. of Math. 2010.

5.2 Andrea L. Bertozzi (bertozzi@math.ucla.edu)

PROFESSIONAL PREPARATION _____.

PRINCETON UNIVERSITY A. B. in Mathematics, Summa cum Laude, 1987

A. M. in Mathematics, 1988, Ph. D. in Mathematics, 1991

UNIVERSITY OF CHICAGO L. E. Dickson Instructor and NSF Postdoc, 1991-5

APPOINTMENTS _____.

UNIVERSITY of CALIFORNIA LOS ANGELES Professor of Mathematics 2003-present, Director of Applied Mathematics, 2005-present.

DUKE UNIVERSITY Professor of Mathematics and Physics 1999-2004

Associate Professor of Mathematics, 1995-1999

ARGONNE NATIONAL LABORATORY Maria Geoppert-Mayer Distinguished Scholar, 95-6

SYNERGISTIC ACTIVITIES _____.

1. PI on NSF workforce grant, overseeing training program for 30 REU students each year, including several projects of interest to ONR.

2. Membership on journal editorial boards: Applied Mathematics Research eXpress, SIAM J. Math. Anal., Advances in Differential Equations, Mathematical Models and Methods in the Applied Sciences (M3AS), Multiscale Modeling and Simulation (SIAM), Nonlinearity, Interfaces and Free Boundaries.

3. Chair of Scientific Advisory Board, Institute for Computational and Experimental Research in Mathematics, Brown University.

4. Plenary talks at: AMS-SIAM-MAA Joint Meetings-San Antonio 1999, Atlanta 2005, and New Orleans 2011, ICIAM 2011, ANZIAM (Australia) 2011, SIAM Materials Meeting-1999, SIAM 50th Anniversary Annual Meeting-2002, SIAM Annual Meeting - Boston 2006, European Consortium on Mathematics in Industry, London 2008, SIAM Conf. Nonlinear Waves, Rome 2008, Sonia Kovalevsky Lecture SIAM 2009.

HONORS AND AWARDS _____.

Elected American Academy of Arts and Sciences, 2010

Elected SIAM Fellow, 2010

Sonia Kovalevsky Prize, SIAM, 2009

Presidential Early Career Award for Scientists and Engineers, 1996-2001

Young Investigator Award, Office of Naval Research, 1996-9

Alfred P. Sloan Research Fellowship 1995-9

5.3 Lawrence Carin (lcarin@ee.duke.edu)

Education

Ph. D. in Electrical Engineering, August 1989
University of Maryland
College Park, MD

M.S.E.E., December 1986
University of Maryland, College Park

B.S.E.E., May 1985
University of Maryland, College Park

Employment

William H. Younger Professor of Engineering, 7/1/03 to present
Duke University

Co-Founder and Director of Technology, 5/1/05 to present
Signal Innovations Group, Inc., Durham, NC

Associate Professor and Professor, 8/1/95-6/30/03
Department of Electrical Engineering
Duke University
Durham, N.C.

Assistant Professor and Associate Professor, 9/1/89-7/31/95
Department of Electrical Engineering
Polytechnic University
Brooklyn, N.Y.

Honors

William H. Younger Distinguished Professor of Engineering (2003)
IEEE Fellow (2001)
DoD SERDP Cleanup Project of the Year (2000, 2005 and 2009)
National Science Foundation Research Initiation Award (1992)
Tau Beta Pi and Eta Kappa Nu

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RESEARCH & RELATED Senior/Key Person Profile

PROFILE - Project Director/Principal Investigator

Prefix:	Dr.	* First Name:	Stanley	Middle Name:	
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* Attach Biographical Sketch	SJO_Bio1017029034.pdf	Add Attachment	Delete Attachment	View Attachment	
Attach Current & Pending Support		Add Attachment	Delete Attachment	View Attachment	

PROFILE - Senior/Key Person 1

Prefix:	Dr.	* First Name:	Andrea	Middle Name:	
* Last Name:	Bertozzi	Suffix:			
Position/Title:	Professor	Department:	Mathematics		
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Credential, e.g., agency login:					
* Project Role:	Co-PD/PI	Other Project Role Category:			
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Attach Current & Pending Support		Add Attachment	Delete Attachment	View Attachment	

ADDITIONAL SENIOR/KEY PERSON PROFILE(S)

	Add Attachment	Delete Attachment	View Attachment
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Additional Biographical Sketch(es) (Senior/Key Person)

	Add Attachment	Delete Attachment	View Attachment
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Additional Current and Pending Support(s)

	Add Attachment	Delete Attachment	View Attachment
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OMB Number: 4040-0001
Expiration Date: 04/30/2008

5.2 Andrea L. Bertozzi (bertozzi@math.ucla.edu)

PROFESSIONAL PREPARATION _____.

PRINCETON UNIVERSITY A. B. in Mathematics, Summa cum Laude, 1987

A. M. in Mathematics, 1988, Ph. D. in Mathematics, 1991

UNIVERSITY OF CHICAGO L. E. Dickson Instructor and NSF Postdoc, 1991-5

APPOINTMENTS _____.

UNIVERSITY of CALIFORNIA LOS ANGELES Professor of Mathematics 2003-present, Director of Applied Mathematics, 2005-present.

DUKE UNIVERSITY Professor of Mathematics and Physics 1999-2004

Associate Professor of Mathematics, 1995-1999

ARGONNE NATIONAL LABORATORY Maria Geoppert-Mayer Distinguished Scholar, 95-6

SYNERGISTIC ACTIVITIES _____.

1. PI on NSF workforce grant, overseeing training program for 30 REU students each year, including several projects of interest to ONR.

2. Membership on journal editorial boards: Applied Mathematics Research eXpress, SIAM J. Math. Anal., Advances in Differential Equations, Mathematical Models and Methods in the Applied Sciences (M3AS), Multiscale Modeling and Simulation (SIAM), Nonlinearity, Interfaces and Free Boundaries.

3. Chair of Scientific Advisory Board, Institute for Computational and Experimental Research in Mathematics, Brown University.

4. Plenary talks at: AMS-SIAM-MAA Joint Meetings-San Antonio 1999, Atlanta 2005, and New Orleans 2011, ICIAM 2011, ANZIAM (Australia) 2011, SIAM Materials Meeting-1999, SIAM 50th Anniversary Annual Meeting-2002, SIAM Annual Meeting - Boston 2006, European Consortium on Mathematics in Industry, London 2008, SIAM Conf. Nonlinear Waves, Rome 2008, Sonia Kovalevsky Lecture SIAM 2009.

HONORS AND AWARDS _____.

Elected American Academy of Arts and Sciences, 2010

Elected SIAM Fellow, 2010

Sonia Kovalevsky Prize, SIAM, 2009

Presidential Early Career Award for Scientists and Engineers, 1996-2001

Young Investigator Award, Office of Naval Research, 1996-9

Alfred P. Sloan Research Fellowship 1995-9

5 Qualifications

5.1 Stanley J. Osher (sjo@math.ucla.edu)

University of California at Los Angeles
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Professional Preparation

Brooklyn College Physics B.S. 1962
New York University Mathematics M.S. 1964
New York University Mathematics Ph.D. 1966

Appointments

1977-Present Professor, UCLA, Department of Mathematics
1975-1977 Professor, SUNY, Stony Brook, 1975-77
1970-1975 Associate Professor, SUNY, Stony Brook
1968-1970 Assistant Professor, University of California Berkeley
1966-1968 Assistant-Associate Mathematician, Brookhaven National Laboratories

Synergistic Activities

1. Coinventor and a principle developer of i) state-of-the-art high resolution schemes for hyperbolic conservation laws and Hamilton-Jacobi equations; ii) level set methods for moving fronts involving topological changes iii) total variation and other partial differential equations based image processing techniques, iv) fast algorithms for L1 type optimization. His work has been in the scientific and international media, e.g. science News, Die Zeit.
2. He has had approximately 60 invited lectures in the past two years.
3. He is or was recently associate editor of 11 journals.
4. He was co-organizer of several long meetings at the NSF-funded Institute for Pure and Applied Mathematics (IPAM) at UCLA.
5. He is Director of Special Projects at IPAM and has a joint faculty appointment with UCLAs Electrical Engineering and Computer Science Departments.
6. He has co-founded three successful companies, each based largely on his own research.
7. He has graduated over 50 Phd students and mentored over 45 postdoctoral fellows.

Achievements and Honors Fulbright Fellow, 1971 Alfred P. Sloan Fellow, 1972-1974 SERC Fellowship (England), 1982 US-Israel BSF Fellow, 1986 NASA Public Service Group Ach. Award, 1992 Invited speaker, Int. Cong. Math., Zurich, 1994, ICI Original Highly Cited Researcher, 2002, Japan Soc. of Mech. Eng., Comp. Mech. Award (2002), ICIAM Pioneer Prize, 2003, Elected to US Nat. Acad. of Sci., 2005, SIAM Ralph E. Kleinman Prize, 2005, Docteur Honoris Causa, ENS Cachan, France 2006 US Ass. for Comp. Mech. Comp. and Appl. Sci. Award, 2007, SIAM Fellow 2009, Elected to the Am. Acad. of Arts and Sci., 2009, Honorary Doctoral Degree Hong Kong Baptist University 2009, SIAM Fellow 2009, plenary speaker Int. Cong. of Math. 2010.